#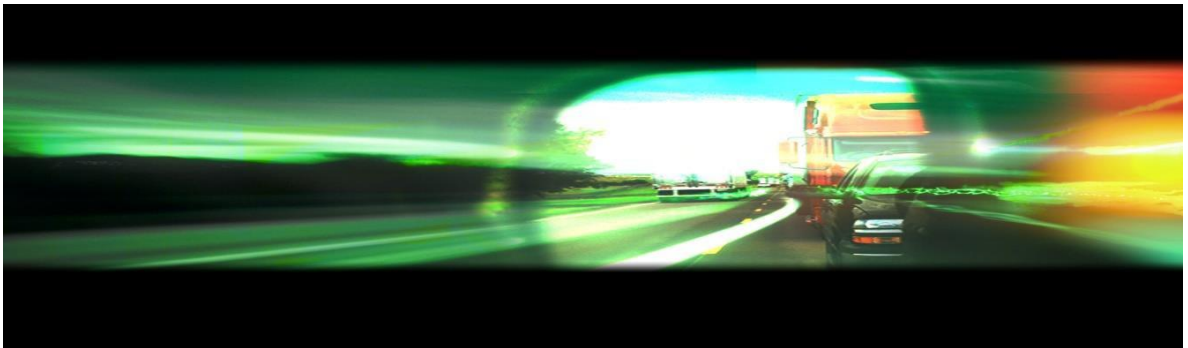 Use Driving Simulator to Synthesize the Related Vehicle Specific Power (VSP) for Emissions and Fuel Consumption Estimations

Final Report

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16. Abstract

Driving simulator approach can readily incorporate drivers' real driving behaviors, the essential parameter that influences emissions. With regard to this, this research is proposed to test and validate the feasibility and applicability of the driving simulator approach in producing vehicle activity data, thus generating vehicle specific power (VSP) values for estimating the emissions. A test scenario was developed for the driving simulator based on real world network parameters. Twenty drivers participated in the driving simulator tests. Each participant drove both a vehicle in the real world network and the driving simulator in the lab environment to ensure consistent driving behaviors. The
test results demonstrated that the difference between operating mode distributions from real world driving versus driving simulators no more than 5%. The operating mode distributions in the two tests were highly correlated to each other (R 0.95) and posed statistically significant indistinctive. The average relative difference in total emissions was only around 2% to 3%. Based on the analysis results as well as the feedback survey from the 20 participating drivers, the study concludes that the driving simulator is a feasible experimental tool for developing VSPs, and thus for estimating vehicle emissions, especially for scenarios where the driving time is relatively short, and network and traffic conditions are less complex. Besides, a fuzzy logic based Table Look-Up Scheme was designed to calibrate the operating mode distributions from the simulator. Results show that the calibration errors of estimated emissions can
be reduced to about 50% of the total emission, while the validation error of overall emissions is less than 2%. The approach was tested in two cases, which demonstrates that it is applicable to estimate vehicle emissions using the driving simulator tests.

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ABSTRACT

Driving simulator has been widely applied in studies related to the road geometric design, driving behavior and traffic safety, but its application to the study of emissions rarely has been reported. Unlike the traditional traffic simulation approach, the driving simulator approach can readily incorporate drivers' real driving behaviors, the essential parameter that influences emissions. This research strives to test and validate the applicability of the driving simulator approach in producing vehicle activity data, thus generating vehicle specific power (VSP) values for estimating the emissions. A test scenario was developed for the driving simulator based on real world network parameters. Twenty drivers participated in the driving simulator tests. Each participant was required to drive both a vehicle in the real world network and the driving simulator in the lab environment to ensure consistent driving behaviors. The test results demonstrated that the difference between operating mode distributions from real world driving versus driving simulators no more than 5%. Correlation analysis and significance testing were then conducted to examine whether such difference was statistically acceptable. The results indicate that the two operating mode distributions are highly correlated, and the average relative difference of total emissions is only around 2% to 3%. Based on the analysis results as well as the feedback survey from the 20 participating drivers, the study concludes that the driving simulator is a feasible experimental tool for developing VSPs, and thus for estimating vehicle emissions, especially for scenarios where the driving time is relatively short, and network and traffic conditions are less complex.

In order to make full use of the driving simulator data for emission estimation, a fuzzy logic based Table Look-Up Scheme was designed to calibrate the operating mode

distributions from the simulator. The modeling results show that the calibration errors of estimated emissions can be reduced to about 50% of the total emission, while the validation error of overall emissions is less than 2%. Results show that the operation data (e.g. speed, acceleration, VSP) from the driving simulator can be used for vehicle emission estimation if these data are well calibrated though the proposed Fuzzy Table Look-up Scheme. Furthermore, two case studies of vehicle emissions were conducted in a simulated work zone with pedestrian crossing and a signalized intersection with sun glare disturbance, which demonstrated that it is feasible to estimate vehicle emissions using the operation data collected by a driving simulator test.

EXECUTIVE SUMMARY

This research is proposed to study the feasibility and applicability of a driving simulator approach to estimate vehicle emissions, by a comparative study, fuzzy logic calibration, and two case studies. A comparative study of estimated vehicle emissions was conducted between driving on real roads and in a fictitious driving environment in the lab of Texas Southern University.

A high fidelity 360 degree visual displays driving simulator was used in the simulator test in the lab. The test routes, traffic flow, and road parameters in the driving simulator test were designed to be similar to those in the real-road test for consistent driving behaviors. Besides, a fuzzy logic based Table Look-Up Scheme was adopted to calibrate the Operating Mode distributions from the simulator for more accurate estimation. Lastly, the simulator approach with calibration was applied in two cases of conflicting areas, a work zone with pedestrian crossing and a signalized intersection with sun disturbance.

More specifically, twenty drivers were recruited for an on-road driving test as well as a driving simulator test in the lab environment. Drivers' driving behaviors in the two driving tests were collected, including acceleration and speed, which were used to calculate Vehicle Specific Power (VSP) for emission estimation. The operating mode distributions between the two driving tests were compared, which showed that there was no more than 5 % difference and they are highly correlated (R=0.95). The little difference was attributed by the various reasons, such as dynamic traffic in the real road test, different accelerator of the test vehicles, different sensitivity of the brake pedal, less distraction in the driving simulator tests, and so on. Even though the distribution of the operating mode ID 22, 23, and 35 posed relatively more different between the two tests,

comparing with other IDs, the statistically significant differences of them were indistinctive (p-value_22: 0.073; p-value_23: 0.052; p-value_35: 0.180). Furthermore, there were only 2% to 3% relative differences in total emissions estimated in the two tests. Besides, 90% of the test drivers felt little difference between driving on the real roads and the fictitious environment, but 65% of them found difficult to concentrate on the driving simulator test after 15 to 20 minutes driving. Due to the safety nature of the simulator test, test drivers performed higher speed in the driving simulator test than on the real road for their less precaution. Therefore, it could be concluded that the driving simulator is a feasible experimental tool to develop VSPs for estimating vehicle emissions, especially for the scenario where the driving time is relatively short, and network and traffic conditions are less complex.

To overcome the slight difference between the two tests and use the driving simulator collected data more practical for vehicle emissions estimation, the operating mode distributions from the driving simulator test were calibrated by a fuzzy logic based Table Look-Up Scheme. With the calibrated operating mode distribution, the difference in estimated total emissions between the two tests became obviously smaller, 50% less than before, while the validation error of overall emissions was less than 2%. Thus, the operation data (e.g. speed, acceleration, VSP) from the driving simulator could be used for vehicle emission estimation, and a Fuzzy Table Look-up Scheme based calibration of the simulator operation data could lead to a more accurate estimation.

Lastly, the proposed simulator approach was applied in two cases: a work zone with pedestrian crossing, and a signalized intersection with sun glare disturbance. Thirty subjects participated in the driving simulator tests. Their vehicle activity data were

calibrated by a designed Fuzzy Logic based Table Look-Up Scheme and then used to calculate the VSP for total emission estimation. Results show that it is applicable to estimate vehicle emissions using the driving simulator approach and the estimated emission results were relative reasonable.

Further studies with more test drivers from diverse socio-demographic groups were recommended to explore factors that may influence the test results in a driving simulator test. More tests shall be conducted to validate the applicability of the driving simulator approach for emission estimation. Besides, a more accurate calibration method could be designed for the vehicle emissions on freeway and on local roads, respectively.

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CHAPTER 1

INTRODUCTION

1.1 Background of Research

The transportation sector has increasingly become a major source of air pollution due to the growth of motorization during the past decades. According to Rodrigue et al. (2013), 70%-90% of emitted carbon monoxide emissions result from transportation activities, which also account for the production of 45%-50% of nitrogen oxides and 40%-50% of total hydrocarbon emissions. Further, it was demonstrated in the report of the U.S. Environmental Protection Agency (EPA) (2012) that 13% of 2010 global carbon dioxide emissions (the principal cause of global warming) emanate from the transportation sector. In the U.S., transportation activities accounted for 27% of 2010 total carbon dioxide emissions, which was much higher than the level in other countries. On-road vehicles are the overriding source of transportation-related emissions, accounting for almost 80%. Recent studies have shown that the Vehicle Specific Power (VSP), which is the sum of the loads resulting from aerodynamic drag, acceleration, rolling resistance, and hill climbing, all divided by the mass of the vehicle, is a critical variable in estimating vehicle emissions. In practical applications, VSP can be obtained directly from basic traffic variables, including the instantaneous speed and acceleration. The concept of the operating mode is further defined in the multi-scale Motor Vehicles Emission Simulator (MOVES) in terms of VSP and instantaneous speed, which are directly linked to emission rates. The operating mode distribution is a concept used to

characterize different driving and traffic conditions by binning the operating mode values.

In recent years, many studies have used traffic simulation models to generate vehicle and network wide emission estimations. Research has shown that emissions based on such an approach are not very accurate. The fundamental reason is that most of existing traffic simulation models cannot provide detailed and reliable representations of traffic variables, such as instantaneous speed and acceleration, which are critical to the accurate evaluation of vehicle emissions. Driving simulators have been used widely in recent years for various purposes, especially for traffic engineering and traffic safety studies. However, we have not found any application of driving simulators in emissions studies. Therefore, this study strives to test and validate the applicability of the driving simulator approach in producing vehicle activity data, thus generating vehicle specific power (VSP) values for estimating emissions. The VSP-based binning approach provided by MOVES is utilized to calculate and compare the differences between emissions produced from real-world driving tests and the driving simulator tests. Using VSPs and the corresponding vehicle activity data, operating mode distributions can be obtained. A testing scenario is designed for the driving simulator based on real-world road traffic parameters. Each test driver drives both a vehicle on the real world roadways and the driving simulator in a lab environment to ensure consistent driving behaviors. By deriving VSPs from both real world and simulated vehicle activity data, it is possible to compare operating mode distributions, as well as vehicle emissions.

1.1.1 Overview of the Study on Driving Simulator

Driving simulators are used for entertainment as well as in driver's education courses. They are also used for research purposes in the area of human factors and medical research to monitor driver behavior, performance, and attention, and in the car

industry to design and evaluate new vehicles or new Advanced Driver Assistance Systems (ADAS).

There are two types of Driving Simulators. One is the Modular design simulator, which has interchangeable cabs, and can be configured to replicate tractor/trailer trucks, dump trucks and other construction vehicles, airport-operated vehicles, emergency response and police pursuit vehicles, buses, subway trains, passenger vehicles, and heavy equipment such as cranes. The other type is the multi-station driving simulator. This type of simulator enables one instructor to train several drivers at one time. These systems are equipped with instructor stations that control all driving stations. The advantage of the multi-station simulator is the reduction in time and cost from training large numbers of drivers at the same time.

Driving simulators are used at research facilities for many purposes. Qiao et al., (2014) used a driving simulator to examine the effectiveness of a Drivers' Smart Assistance System (DSAS). Meanwhile, a driving simulator has been adopted to study drivers' driving behaviors in a work zone, at a signalized intersection with sun glare disturbance, and drivers' responses to different types of warning messages provided by a smartphone app have been studied by driving simulator tests (Li et al., 2015a; Qiao et al.,

2016; Li et al., 2015b). In addition, driving simulators allow researchers to study driver behavior under conditions that would be illegal and/or unethical in a real driving situation. For instance, studies on driver distraction would be dangerous and unethical if done on the road because of the inability to obtain informed consent from other drivers. With the increasing use of various in-vehicle information systems (IVIS) such as satellite

navigation systems, cell phones, DVD players and e-mail systems, simulators play an important role in assessing the safety and utility of such devices.

Fidelity. There are many research driving simulators, with a wide range of capabilities. The most complex ones, such as the National Advanced Driving Simulator, have a full-sized vehicle body, with six-axis movement and 360-degree visual displays. On the other end of the range, there are simple desktop simulators, such as the York Driving Simulator, that are often operated using a computer monitor for the visual display, a videogame-type of steering wheel and pedal input devices. These low cost simulators are used readily in the evaluation of basic and clinically oriented scientific questions. The issue of quality is complicated by political and economic factors, as facilities with low- fidelity simulators claim their systems are "good enough" for the job, while the high- fidelity simulator groups insist that their (considerably more expensive) systems are necessary. Research on motion fidelity indicates that, while some motion is necessary in a driving simulator, it does not need to have the range to match real-world forces. Recent research studies have also considered the use of real-time photo-realistic video content that reacts dynamically to driver behaviors in the environment.

Validity. There is a question of validity—whether results obtained in the simulator are applicable to real-world driving. Given the inability to replicate some simulator studies on the road, this is likely to remain an issue for some time. Some research teams are using automated vehicles to recreate simulator studies on a test track, enabling a more direct comparison between the simulator study and the real world. As computers have grown faster and simulation is more widespread in the automotive industry, commercial vehicle math models that have been validated by manufacturers are being used in

simulators. Driving simulators can also be used for to train drivers of airplanes, trains, trams and other vehicles. The simulation software could be viewed as educational games, and some companies have become specialists for the delivery of simulator systems.

Simulator Adaptation Syndrome (SAS). Simulator Adaptation Syndrome is an issue with all simulators, not just driving simulators. The main cause of SAS is system delays between the driver's command and the response of the simulator. In effect, the brain, referencing driving a real vehicle, expects the simulator's response to be the same as a car, so the greater the deviation, the greater the "adaption burden" on the brain. If the deviation is large, the driver may experience headaches, motion sickness, disorientation, etc., although this is very dependent on the individual. Likewise, the simulator "cues" also have an effect that is some individuals will experience discomfort due to a simulator not having motion cues, where others may not have a problem with such simulators. Some individuals will show high tolerance to visual system delays, where others may not.The "Adaptation" in SAS relates to the brain's accepting these simulator's disparities relative to a real vehicle and thus slowly changing its reference point to that of the simulation. Thus, with gradual introduction to the simulator environment, the brain will slowly adapt, and the negative effects of SAS (headaches, motion sickness, disorientation, etc.) will be greatly reduced. Ironically, once a person spends several hours in a driving simulator, a real vehicle can evoke SAS again; however, the adaption time is greatly reduced, as the brain quickly "remembers" and "resets" the real vehicle reference point. As an example of SAS timing, when airline pilots go through the regular simulator training, they are not allowed to fly an airplane for one week in order to allow their brains to "forget" the SAS reference point induced by the simulator.

1.1.2 Portable Emission Measurement System (PEMS)

The research in this study requires the use of emission measurement technology to establish an emission database composed of real-world data for the purpose of emissions estimation. Presently, there are four available emission measurement technologies: Chassis Dynamometer Test, Tunnel Test, Remote Sensing, and PEMS.PEMS has been proved the more convenient tool among the four technologies due to its advantages in collecting emission data during the actual use of vehicles in their regular operations. Thus, it has been applied to collect emission data in the majority of recent emission testing efforts. This study used OEM-2100AX Axion (2010), which is one of the most advanced PEMS products in the market today, as the primary emission data collection tool. This equipment is composed of four main subsystems: computer, engine data acquisition module, PM monitor, and dual gas analyzers. Using OEM-2100AX Axion, emissions and vehicle speed, as well as the temperature and engine resolution per minute (RPM), can be reported instantaneously. The installation of Axion equipment and its data collection operation interface are shown in Figure 1.

FIGURE 1 Axion Equipment and its Operation Interface

1.1.3 Vehicle Specific Power and Operating Mode-based Approach

An important concept used in this research is the vehicle specific power (VSP),which is the tractive power by a vehicle to move itself and its cargo or passengers (Namand Giannelli, 2005). The VSP value for light-duty vehicles is calculated by Equation (1),which is derived from the results obtained by Jiménez-Palacios (1999):

$$VSP = v * 1.1 * a + 9.81 * grade(\%) + 0.132\ v + 0.000302 * v^3 \tag{1}$$

Where v is the second-by-second vehicle speed in the unit of m/s, a is the second-by-second acceleration in the unit of $m/s2$, and *grade (%)* is the vehicle vertical rise divided by the slope length, which can be assumed to be zero where the terrain is flat. Since the test areas in this research in Houston are flat, the *grade* is assumed to be zero. Then, the VSP equation can be simplified as follows:

$$VSP = v * (1.1 * a + 0.132) + 0.000302 * v^3 \tag{2}$$

In this equation, the second-by-second speed and acceleration data are the two major variables that determine the value of VSP. Incorporating VSP into the emission modeling approach (VSP-based emission modeling approach) is useful because (1) VSP is an effective parameter to estimate vehicle emissions because of its direct physical interpretation and strong statistical relationship with vehicle emissions (Song et al., 2010); and (2) VSP can be easily estimated by second-by-second speed and acceleration. This VSP-based approach has been applied widely in emissions estimation during the past dozen years.

The basic methodology of the VSP-based approach is binning second-by-second VSP data and computing the average emission rate in each bin (Shi and Yu, 2011). The meaning of each VSP bin is the percentage of its corresponding VSP values in the whole VSP distribution, which is the indicator to describe the statistical distribution characteristics of all of the VSP bins. Upon VSP distribution, the emissions in each bin can be captured for the specific emission process.

The accuracy of the VSP-based approach is dependent upon how VSP bins are defined (Shi and Yu, 2011).However, there has been a lack of distinct definition of VSP bins. EPA defined a new variable—operating mode, embedded in Motor Vehicle Emission Simulator (MOVES), which combines the VSP and the instantaneous speed. The definition of MOVES operating modes is illustrated in Table 1, in which 23 operating mode bins are clearly defined in terms of VSP and instantaneous speed. The meaning of each operating mode bin is the percentage of its corresponding VSP, speed or acceleration values in the whole operating mode distribution. This distribution is the indicator that describes the statistical distribution characteristics of all of the operating

mode bins and thus can reflect the dynamic vehicle activity conditions. The operating mode-based emission modeling approach incorporates operating modes into the process of emission modeling. The basic methodology of the operating mode-based approach is binning second-by-second VSP and speed to compute operating mode distribution for estimating the average emission rate/factor in each operating mode bin. Accordingly, the second-by-second speed and VSP data are the two major variables to determine the operating mode distributions. Since MOVES is currently regarded as the most widely accepted tool that EPA has for emissions estimation, the operating mode-based approach served for emission estimation in this study.

Table 1 Definition of MOVES Operating Mode Attributes for Running Energy Consumption (MOVES 2010 User Guide)

OperatingMode ID	Operating Mode Name
0	Braking: Acceleration<-2 mph/s, or<-1 mph/s for 3 consecutive seconds
1	Idling: -1<=Speed<1
11	Low Speed Coasting: VSP<0; 1<=Speed<25
12	Cruise/Acceleration: 0<=VSP<3; 1<=Speed<25
13	Cruise/Acceleration: 3<=VSP<6; 1<=Speed<25
14	Cruise/Acceleration: 6<=VSP<9; 1<=Speed<25
15	Cruise/Acceleration: 9<=VSP<12; 1<=Speed<25
16	Cruise/Acceleration: 12<=VSP; 1<=Speed<25
21	Moderate Speed Coasting: VSP<0; 25<=Speed<50
22	Cruise/Acceleration: 0<=VSP<3; 25<=Speed<50
23	Cruise/Acceleration: 3<=VSP<6; 25<=Speed<50
24	Cruise/Acceleration: 6<=VSP<9; 25<=Speed<50
25	Cruise/Acceleration: 9<=VSP<12; 25<=Speed<50
27	Cruise/Acceleration: 12<=VSP<18; 25<=Speed<50
28	Cruise/Acceleration: 18<=VSP<24; 25<=Speed<50
29	Cruise/Acceleration: 24<=VSP<30; 25<=Speed<50
30	Cruise/Acceleration: 30<=VSP; 25<=Speed<50
33	Cruise/Acceleration: VSP<6; 50<=Speed
35	Cruise/Acceleration: 6<=VSP<12; 50<=Speed
37	Cruise/Acceleration: 12<=VSP<18; 50<=Speed
38	Cruise/Acceleration: 18<=VSP<24; 50<=Speed
39	Cruise/Acceleration: 24<=VSP<30; 50<=Speed
40	Cruise/Acceleration: 30<=VSP; 50<=Speed

1.1.4 Applications of Fuzzy Logic Theory

This study chooses Fuzzy Logic Theory to calibrate the operating mode bins distributions as Fuzzy Logic Theory deals with reasoning that is approximate rather than fixed and exact, and emission is a fuzzy value.

Fuzzy Logic Theory, initiated by Lotfi A. Zadeh in 1965 with his seminal paper "Fuzzy Sets", is capable of dealing with systems where the precise descriptions are too complicated to be obtained, and where human knowledge is available to be combined into a system.

The Fuzzy Table Look-up Scheme, which was proposed by Wang, is the first method of designing fuzzy systems automatically from data. It has been used in a variety of transportation applications, including truck backing-up control, time delay estimation at signalized intersections, freight transport assessment, arrow sign placement, crosswalk placement, pedestrian crossings, etc.

Suppose that the following input-output pairs are provided:

$$(x_1^p, x_2^p, \ldots, x_n^p, y^p), p = 1, 2, \ldots, N \tag{3}$$

Where, $(x_1^p, x_2^p, \ldots, xn^p) \in U = [\alpha_1, \beta_1] \times [\alpha_2, \beta_2] \times \ldots \times [\alpha_n, \beta_n] \in R^n$ are all the considered input variables to the sign placement model, while $y_0^p \in V = [\alpha_y, \beta_y \in R]$ is the percentage error used to calibrate the corresponding operating mode distribution. The input variables $(x_1^p, x_2^p, \ldots, x_n^p)$(here n=2 meaning that there are two input variables) are VSP and speed V. *p* is the *p*-th collected data pair. The proposed fuzzy system should be based on the rule generated from these two input-output pairs. The following five-step scheme can be used to design the fuzzy system.

Define the Fuzzy Sets to Cover the Input and Output Spaces. Specifically, for each fuzzy set, define N fuzzy sets A_i^j ($j = 1,2, \ldots , N_i$), which are required to be complete in $[\alpha, \beta]$, that is, $[\alpha, \beta]$ ($i = 1, 2, \ldots , n$) for any $x \in [\alpha, \beta]$, there exists A such that its membership values $\mu(x) \neq 0$. For example, the pseudo-trapezoid membership functions are possible candidates. Generate one rule from one input-output pair. First, for each input-output pair $(x_1^p, x_2^p , \ldots , x_n^p, y^p)$, determine the membership values of x_i^p ($x = 1,2, \ldots , N_i$) in fuzzy sets A_i^j ($j = 1,2, \ldots , N_i$) and the membership values of y^p in fuzzy sets B^l ($l = 1,2, \ldots , N_y$) . That is, compute $\mu_{A_i}^j (x_i^p)$ for ($j = 1,2, \ldots , N_i$) , $i = 1, 2, \ldots , n \mu B^l (yp)$ and for $l = 1,2, \ldots , N_y$. Then for each input variable x_i ($i = 1, 2, . . . , n$) , determine the fuzzy set in which x_i^p has the largest membership value, that determines A such that $\mu_{A_i}^j (x_i^p) \geq \mu_{A_i}^j (x_i^p)$, $j = 1, 2, \ldots , N_i$. Similarly, determine B such that $\mu_B^{l*} (yp) \geq \mu Bl (y^p)$, $l = 1, 2, \ldots , N_y$. Then we can obtain a fuzzy IF-THEN rule.

$$Ru: IF \ x_1 \ is \ A_1^l \ and \ \ldots \ and \ x_n \ is \ A_n^l \ , THEN \ y \ is \ B^l \tag{4}$$

Assign a Degree to Each Rule Generated. There are possibly conflicting rules, thus a degree is assigned to each rule so that only one rule is kept that has the maximum degree. The degree of the rules is determined by the reliability of associated input-output pairs. Therefore, providing the input-output pair $x^p; y^p$ has a reliable degree $\mu^p \in [0,1]$; the degree of the rule generated by $x^p; y^p$ is calculated by:

$$D \ (rule) = \pi_{i=1}^n \ \mu A_i^j {}_* (x_i^p) \ \mu_{B^{l*}}(y^p) \mu^p \tag{5}$$

Create the Fuzzy Rule Base. Possible linguistic rules from human experts (due to conscious knowledge), together with the rules from the input-output pairs, will generate the desired rule base, which forms a look-up table. The entire process can be viewed as a table look-up scheme.

Construct the Fuzzy System Based on the Fuzzy Rule Base. Based on the rule base, a fuzzy system eventually can be constructed with the product inference engine, singleton fuzzifier, and center average defuzzifier:

$$f(x) = \frac{\sum_{l=1}^{M} \bar{y}^l \left(\prod_{i=1}^{n} \mu_{A_i^l}(x_i) \right)}{\sum_{l=1}^{M} \left(\prod_{i=1}^{n} \mu_{A_i^l}(x_i) \right)} \tag{6}$$

Where, $\bar{y}$ is the center value of the fuzzy set B^l in the output region, that is, the THEN part, for the l-th rule. $\mu_A(x_i)$ is the membership function of the l-th rule for the i-th component of the input vector. M is the total number of fuzzy rules.

1.2 Objectives of Research

The background of the research presented above provided the context to define the objectives of this research. The research objectives are summarized as follows:

1. Analyze the operating mode distribution characteristics of real-world and driving simulator scenarios;

2. Calibrate the driving simulator data using Fuzzy Logic Theory and compare the results with the real-world data;

3. Analyze the total emissions of the real world, driving simulator, and calibration results;

4. Studying vehicle emissions estimated by the VSP collected using a driving simulator in a work zone and a signalized intersection with sun glare disturbance.

1.3 Outline of the Study

This research is comprised of six chapters. The first chapter provides an overview of the problems, the research objectives, and the layout of the study. The second chapter presents a literature review of the existing research on driving simulators, as well as the application of Fuzzy Logic Theory. The third chapter describes the design of the study by introducing the data collection method, including the real-world and driving simulator data that are used for the analysis. The fourth chapter presents and analyzes the results of the operating mode distributions, emissions, and calibration. Then the fifth chapter demonstrates two case studies of the vehicle emissions using the driving simulator approach, including a work zone and an intersection with sun glare disturbance. Finally, the sixth chapter provides the study conclusions and recommendations for future research.

CHAPTER 2

LITERATURE REVIEW

The literature review is conducted from three perspectives in order to establish the context for the proposed research. First, the existing studies related to the application of driving simulators will be presented. Second, the study on emission analysis using the operating mode-based approach will be presented. Third, will be an overview of the application of Fuzzy Logic Theory for the calibration. Finally, the limitations of the existing studies will be discussed.

2.1 Applications of Driving Simulator

Driving simulators have been widely used in recent years for various purposes, especially for traffic engineering and traffic safety studies. The study by Stuart et al. (2002) examined the behavioral validation of an advanced driving simulator for its use in evaluating speeding countermeasures, which was performed for mean speed. In this research, all the drivers were mature; 24 participants drove an instrumented car and 20 participants drove the simulator in two separate experiments. Participants all drove on roads with transverse rumble strips at three sites and three equivalent control sites. These scenarios mainly considered deceleration, the approaches to stop sign intersections, right curves, and left curves. Then this study analyzed the numerical correspondence, relative correspondence, and interactive relative validity, the latter using correlations developed from canonical correlation. After the analysis, the result showed that the drivers always drove faster in the instrumented car than in the simulator. Because the scenarios in both the instrumented car and simulator experiments were almost the same, the study concluded that the simulator data could not be used for the establishment of mean speed.

A study conducted by Jorge et al. (2005), confirmed that driving simulators were playing an important role in research concerning human factors and the development of new Advanced Driver Assistance Systems. This research developed a new vehicle dynamics model with ten degrees of freedom. The model was specially designed for real-time applications, mainly driving simulators, and was intended to calculate the motion of a passenger vehicle when driving in normal conditions, representing real vehicle behavior on public roads. In addition, the model also had to present a realistic and predictable behavior in severe driving conditions, such as collision avoidance maneuvers, which could also be of interest when performing simulator experiments. The most important part of this study concerned the model validation. In order to ensure that the vehicle dynamics model behaved like a real car in the conditions mentioned above, predefined maneuvers representing those driving conditions were performed on a test track with a car equipped with data acquisition systems. Moreover, the model was tuned in an attempt to match the test data when performing the same predefined maneuvers. As a result, a comparison was made between the driving simulator and real-world driving to show that the data from the driving simulator were useful for analyzing there response time to traffic lights at intersections for safety issues.

Brook set al.(2005) provided a methodology for evaluating enhanced powered two-wheeler (PTW) conspicuity in a driving simulator environment. In order to evaluate the methodology, 10 European drivers took part in this research, using a specially designed driving simulator scenario. Before the tests, the drivers did not know what the experiment involved, so that the research might be real and convincing. Real-world driving was performed in urban and rural conditions. The drivers were requested to drive in both real

world and simulator scenarios, in both of which, there was a vehicle detection task. The results showed that the motorcycle detection rates were almost the same for both the simulator and the real road, which proved that driving simulator was a powerful tool for driving behavior. Research on daytime lighting treatments and accidents could use these scenarios.

Green(2005) concluded that the driving behaviors and performances in a driving simulator could not substitute for the real conditions. The problems commonly found in the driving simulator related to the quality of the data. To improve the data quality collected by driving simulators, several steps should be taken. These improvements, most of which could be accomplished by simulator manufacturers, would allow driving simulator experiments to resemble the real world more closely and therefore increase their acceptability for research. However, not all of the responsibility was in the hands of simulator manufacturers. Those using simulators needed to be vigilant with regard to the data they collected and to verify that the values reported were indeed reasonable for real driving. This might require some effort to "tune" driving simulators before they are used. Experimenters were encouraged to take the time to "get it right". Driving simulators had an important role to play in human factors and safety research, and that role could continue in the future. Success in that role depended on the credibility of the research results, and as described in this study, results could be enhanced by some simple improvements in driving simulators.

Montella et al. (2011) performed a driving simulator experiment on a real world speed monitoring. In this study, the driving simulator produced a statistically significant mean speed reduction of 12% in the center of the intersection. In the real world

experiment, the mean speed reduction was reduced by 22%. Furthermore, a statistically significant mean speed reduction was observed 150 and 75 m before the intersection. The operating speeds had a similar reduction. Both driving simulator and real world results showed that the intersections significantly affected drivers' speed behavior, even though there were some differences between the two experiments.

In summary, widespread applications of the driving simulator have confirmed that it is indeed an effective and powerful tool to study roadway design, driving behaviors and various safety issues when the massive collection of real world data is technically difficult.

2.2 Emission Analysis with Operating Mode-based Approach

During the past few years, numerous efforts have been made to evaluate vehicle emissions using the operating mode-based approach.

Shi and Yu (2011) assessed the benefits of transportation management strategies in reducing vehicle emissions using the operating mode-based approach. The results showed that signal coordination, high occupancy lanes (HOV), and electronic toll collections (ETC) were all effective strategies to alleviate the production of on-road vehicle emissions. Operating mode-based approach was utilized as well in Tao et al.'s study (2011) to evaluate the effectiveness of signal coordination in reducing emissions during both peak and non-peak hours. The results indicated that such effectiveness was weakened during the transition from non-peak to peak hours. In addition, Tao et al. (2012) also estimated the operating mode distributions under defensive vs. non-defensive driving behaviors and analyzed the effects of these two different behaviors on vehicle emissions,

finding that defensive driving might increase emissions of some pollutants. Wei et al. (2011) evaluated the emission impact of traffic flow operations with the operating mode- based approach, demonstrating that the operating mode distribution was one of the principle traffic flow variables that were highly associated with vehicle emissions. Due to the limitations of collecting real-world instantaneous speed data to generate operating mode distributions for the entire network, Xu et al. (2012) developed an approach to derive operating mode distributions based on the aggregated link average speed data at pre-determined time intervals, which made it easy to estimate emissions at the network level. Yu et al. (2010) developed a city-specific driving schedule based on four types of assessment measurements: Type I, driving activity; Type II, driving operating mode distribution; Type III, fuel consumption rate; and Type IV, the product of Types II and III. The results showed that the driving schedules developed from driving operating mode distribution measurements might result in far more accurate CO_2 emission estimates.

The above studies have demonstrated that the operating mode-based approach is a feasible method to estimate emissions for this study.

2.3 Application of Fuzzy Logic Theory Analysis

Fuzzy Logic Theory is capable of dealing with systems where the input-output relationships are very complex and where human knowledge is accessible to be integrated into the system. The Fuzzy Table Look-up Scheme has proven to be an effective tool for nonlinear modeling.

Zadeh introduced Fuzzy sets in 1965 to represent and manipulate data and information that possess non-statistical uncertainty. Since then, fuzzy logic has been

applied to many fields such as industry, medicine, and economics. The reason for this rapid worldwide growth in the use of fuzzy logic is that it provides an appropriate mechanism to describe the static and/or dynamic behavior of complex physical systems that are difficult analyze with conventional mathematical models. A fuzzy set could be considered as a fuzzy model of human concepts. In a study by Shahida et al. (2011), they considered fuzzy modeling as an approach to form a system model using a description language based on fuzzy logic with fuzzy predicates. The study presented a general approach to modeling an identification of dynamic systems based on fuzzy logic. A table–lookup scheme was presented to generate fuzzy rules from numerical data. This method determined a mapping from input space to output space, based on the combined fuzzy rule base using procedure. They also discussed the application to time series prediction problems.

In Qiao's study (2002), in order to provide sufficient signing information to guide drivers effectively on the highway, the advance guide sign had to be placed wisely. This research employed a state-of-the-art/practice driving simulator in an experiment to evaluate the placement of arrow exit signs on the highway, taking various factors into consideration. The experimental design focused on the effects of traffic flow, highway geometric condition, and human behavior on sign placement. A Fuzzy Table Look-up Scheme was used to build up the rule base of input-output pairs. A fuzzy logic system was constructed based on the outcome from the driving test and survey. Based on the analytical results, the optimal placement of arrow exit signs was recommended under different combinations of input variables.

Fuzzy Logic Theory can be used in the design of intelligent control systems using fuzzy if-then rules that make use of human knowledge and experience to behave in a manner similar to a human controller. Therefore, the level of the mathematical knowledge required is kept basic and the concepts are illustrated with numerous diagrams to aid in comprehension. As a result, all those research that it is curious to be known what are fuzzy concepts and their real-world application will apply in this research.

2.4 Summary

Emissions produced from the transportation sector have been increasing during the past decades, making transportation a major source of urban air pollution. Road topological configurations may affect driving behavior and vehicle activity, and thus result in different productions of emissions. Accordingly, it would be a new breakthrough if we can use driving simulators instead of real cars to do emission research.

As an EPA standard tool for the emissions analysis, MOVES introduced the concept of operating modes, which combined parameters of VSP and the instantaneous speed, and provided the operating mode-based approach for emissions estimation. Existing studies have demonstrated an extensive application of the operating mode-based approach in various emissions analyses, which showed that this approach is feasible for that purpose. Consequently, the operating mode-based approach was also utilized in this research.

Technically, it is impossible to collect massive on-road data for all real world conditions in an emission analysis. As an alternative, a driving simulator was integrated into the data collection. The data generated from the driving simulator can be processed in order to generate the vehicle activity data that are needed for the emissions estimation.

However, it is still not widely used in emissions estimation worldwide because of the questions about the effectiveness of the data. Therefore, the relevance of driving simulator data and real world data needs to be discussed in depth.

CHAPTER 3

DESIGN OF THE STUDY

3.1 Methodology

Figure 2showsthe framework of the entire research process. As illustrated in Figure 2, there are two groups of vehicle activity data to be generated, one from the driving simulator and one from the real world driving experiment.
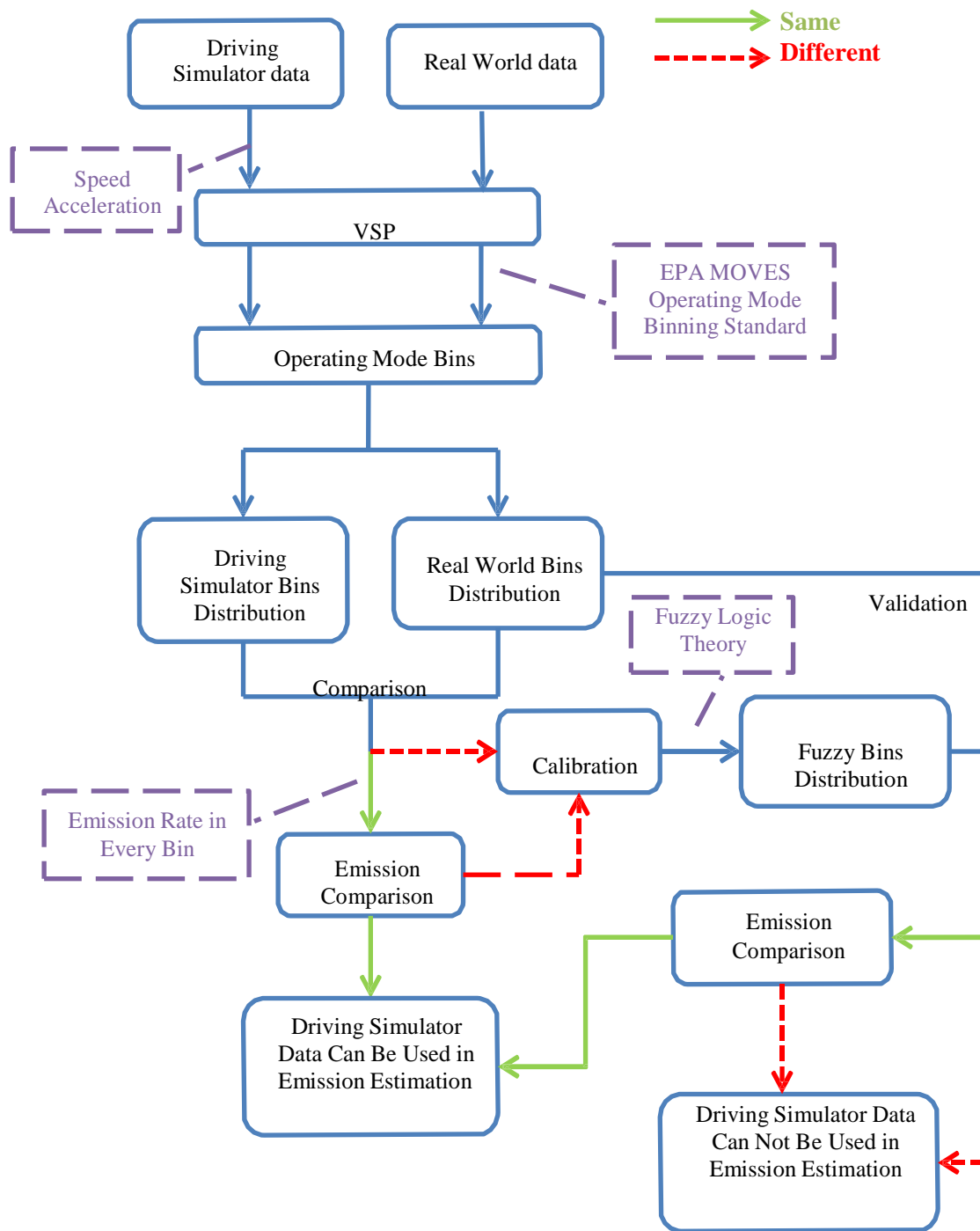
FIGURE 2 Research Framework

Second-by-second speed and acceleration data are used to calculate VSPs. It is noted that based on VSP and the operating mode-binning standard in MOVES, each VSP corresponds to an operating mode bin. By comparing operating mode distributions from the driving simulator with those from the real world, it can be determined whether the results from the driving simulator are acceptable as a proxy for those from the real world. When considerable differences occur, the study will analyze each operating mode ID to identify causes. When two distributions derived from the driving simulator and the real world are sufficiently close, corresponding total emissions are further compared. Based on these analyses, the applicability of using the driving simulator to estimate emissions can be ascertained.

3.2 Scenario Preparation

The study area in this research was defined as a driving route in Houston, starting from the West Garage of Texas Southern University and ending at the East Garage, as shown in Figure 3. The total distance of the route is about 28.5 km, following Blodgett St, Almeda Rd, 610 Loop, Bellaire Blvd, Holcombe Blvd, Old Spanish Trail, and Scott St. The reason for choosing this testing route was that it comprised multiple road classes, including freeway, arterial road and local streets, and crosses multiple land use properties, such as schools, residential and business areas. Thus, it covers a comprehensive set of driving and road conditions.

FIGURE 3 Driving Route for the Test

3.3 Data Collection

3.3.1 Data Collection from Real-World Route

Twenty drivers were recruited from various age and gender groups that participated in the data collection experiments. Each participant was instructed to drive along the study route under the speed limit. The testing vehicle was equipped with a GPS, which collected second-by-second speed and acceleration data needed for calculating VSPs. At each intersection, the signal timing was recorded directly in the GPS. The traffic flow data were found on the Houston TranStar website at http://traffic.houstontranstar.org/layers/ and

http://ttihouston.tamu.edu/hgac/trafficcountmap/, at the time when the driver conducted the test on the real roads. With the VSP and operating mode bins defined by MOVES (Table 1), operating mode distributions were generated.

For the second set of data, second-by-second speed data were collected using a global position system (GPS) device, as shown in Figure 4. The GPS used in this study has a built-in battery and thus can provide power by itself instead of gaining power through the vehicle's cigarette lighter outlet. In addition, the traffic volume was counted manually using both video tape and on-road testing.

FIGURE 4 GPS Used in the Study

3.3.2 Data Collection from Driving Simulator

A driving simulation scenario was developed based on exact traffic and road parameters in the real world study area, such as road types, number of lanes, roadway length, and intersection signal timing. Necessary triggers were set in place at the beginning of each new road type and each intersection, and then the script for each trigger was coded to control the traffic flow, speed limit, and signal timing. Figure 5 is a snapshot of the developed driving simulation scenario.
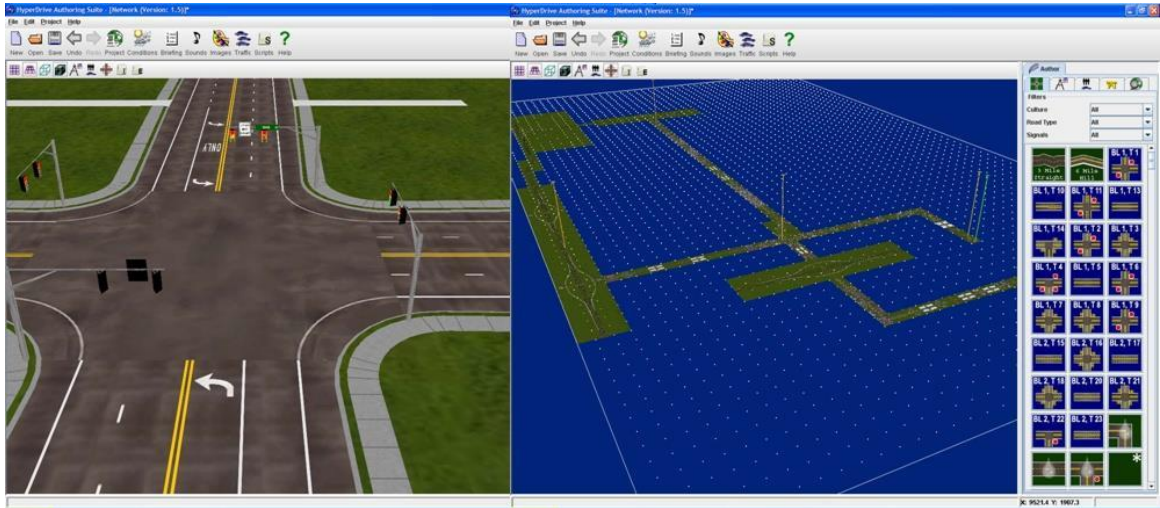
FIGURE 5 Scenario Design in Driving Simulator

The signal timing and traffic flow data were entered in the scenario as inputs. Drivers drove in the driving simulator under the same conditions as they did in the real world in order to ensure consistent driving behaviors. Figure 6 is a snapshot of the driving simulation test.

FIGURE 6 Snapshot of Driving Simulation Test

The driving simulation test resulted in second-by-second driving activity data that were used to calculate VSPs and operating mode distributions. Right after the driving

simulation test, participating drivers were also instructed to complete a questionnaire survey on their subjective feelings about the simulator test.

3.4 Calibration

The next step after the data collection would be to compare the distributions and emissions between field data and driving simulator data. In order to make the driving simulator useful in the vehicle emission estimation, it would be necessary to find a practicable method to calibrate the data from the driving simulator. After an appropriate way of calibrating the operating mode bins distribution, the error may be reduced to make the total emission more or less the same.

The above discussion indicated that traditional calibration methods might not be useful in vehicle emission estimations because the emission with speed and VSP are nonlinear. Since the calibrated results are approximate rather than fixed and exact, Fuzzy Logic Theory has been used in this study.

There are four steps for the Fuzzy Logic Theory:

1. Choose input(speed, VSP) and output(error) data to build the membership functions;
2. Select 15 groups of data to build the rule base and calculate the degree of rule for calibration with average speed, VSP and error of each bin;
3. Calculate the weighted average error for each bin based on the degree of rule and error;
4. Apply the weighted average error for the other five groups of data to calibrate the results.

Figure 7 is an illustration of the pre-determined (MFs) for the inputs and output variables. All the input and output data have two function values called weighting factors. The fuzzy method regards the larger one to be a function value for further research. Each driver's data is recorded on a form with input VSP, speed and output error to calculate the degree of rule for the further calculation as Table 2.

(a)

(b)

MF

N   N   N   Zero   P   P   PL

1.0

0.5

-6   -5   -4   -3   -2   -1   0   1   2   3   4   5   6   Error(%)
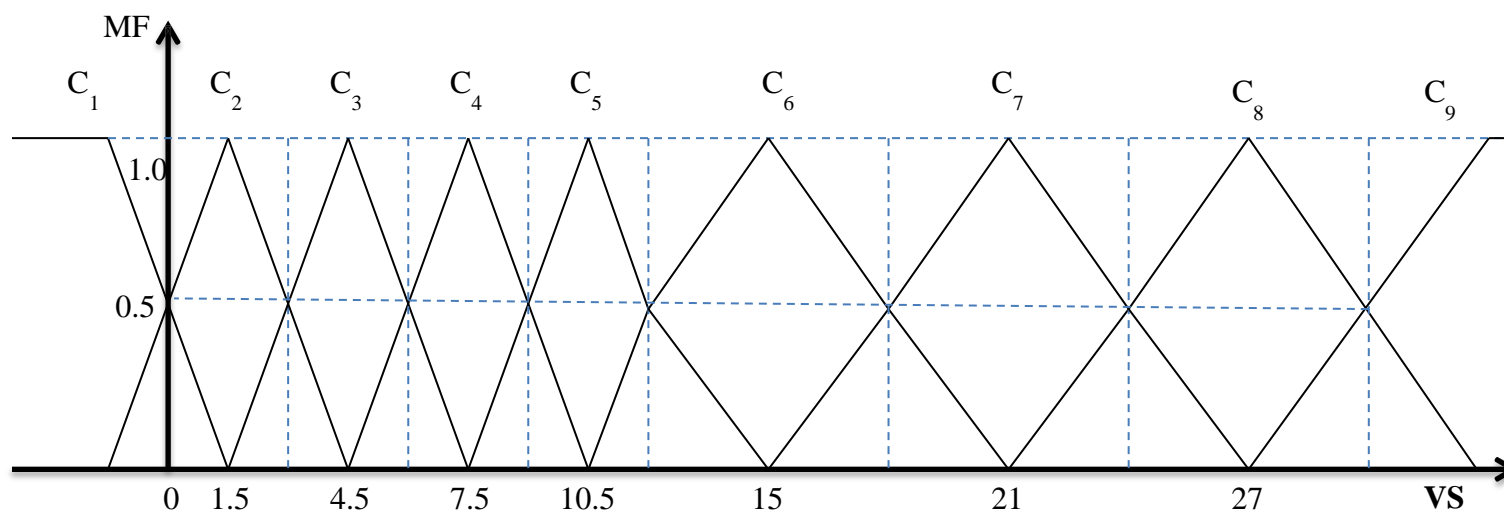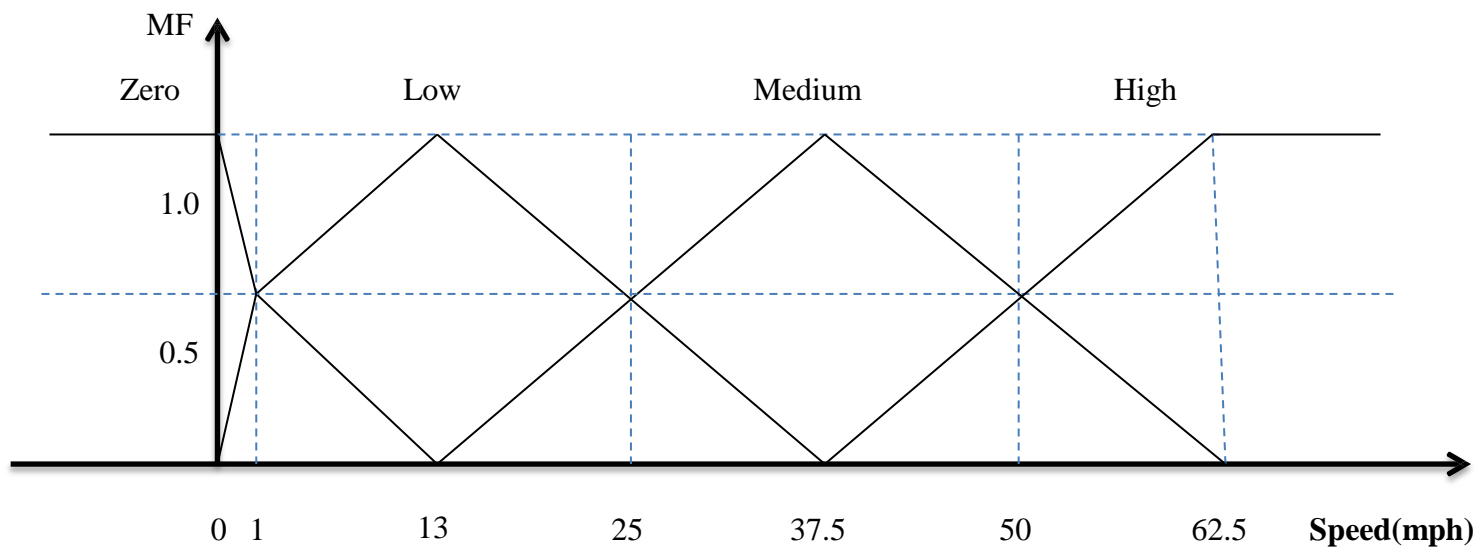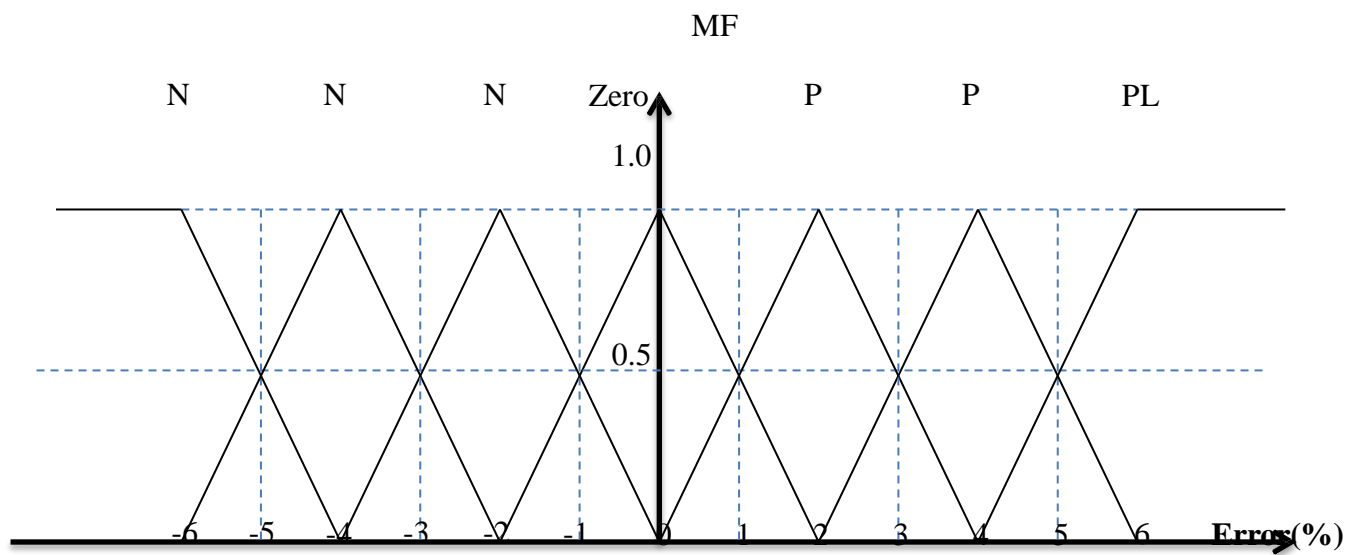
(c)

FIGURE 7 Illustrations of Membership Functions

Table 2 Inputs and Output Variables

| OP Mode ID | Input | | | | | | Output | | | Degree of Rule |
| | VSP | | | V | | | Error (%) | | | |
	Value	Fuzzy numbers	MF	Value	Fuzzy number	MF	Value	Fuzzy number	MF	
0							-2.99	NS	0.505	0.505
1				0.018	Zero	0.991	0.48	Zero	0.761	0.754
11	-2.742	C1	1.000	14.515	L	0.937	2.02	PS	0.991	0.928
12	1.718	C2	0.927	11.462	L	0.936	-2.93	NS	0.535	0.464
13	4.953	C3	0.849	15.612	L	0.891	-2.09	NS	0.956	0.723
14	7.147	C4	0.882	15.395	L	0.900	-1.82	NS	0.910	0.722
15	10.354	C5	0.951	18.829	L	0.757	0.56	Zero	0.721	0.519
16	15.63	C6	0.895	19.613	L	0.724	0.99	Zero	0.503	0.326
21	-6.644	C1	1.000	36.22	M	0.949	-1.14	NS	0.571	0.541
22	2.036	C2	0.821	35.373	M	0.915	-3.60	NM	0.802	0.602
23	4.247	C3	0.916	36.932	M	0.977	11.97	PL	1.000	0.895
24	7.657	C4	0.948	36.29	M	0.952	-0.85	Zero	0.573	0.517
25	10.408	C5	0.969	35.026	M	0.901	-0.43	Zero	0.786	0.687
27	14.443	C6	0.907	35.983	M	0.939	-0.74	Zero	0.631	0.538
28	20.937	C7	0.990	32.503	M	0.800	0.99	Zero	0.506	0.401
29	26.528	C8	0.921	35.478	M	0.919	0.71	Zero	0.645	0.546
30	31.81	C9	0.802	44.062	M	0.738	0.29	Zero	0.853	0.504
33	-1.96	C1	1.000	59.528	H	0.881	-1.16	NS	0.582	0.513
35	8.293	C4	0.736	60.839	H	0.934	1.75	PS	0.873	0.600
37	15.204	C6	0.966	59.575	H	0.883	-1.13	NS	0.566	0.483
38	22.912	C7	0.681	54.129	H	0.665	-1.06	NS	0.531	0.241
39	26.413	C8	0.902	63.242	H	1.000	0.60	Zero	0.699	0.631
40							-0.40	Zero	0.798	0.798

With the membership functions, all the second-by-second data have a degree of rule. The study combines the 15 operating mode bins distributions together, based on the membership function of error and degree of rule, to calculate the relative error of the distribution between real world and driving simulator. That is the value used to calibrate the operating mode bins distributions of driving simulator, listed in Table 3.

Table 3(1) Error Calibration of Operating Mode Bins Distributions

Operating Mode Bins	Driver 1		Driver 2		Driver 3		Driver 4		Driver 5	
	MF of Error	Degree of Rule	MF of Error	Degree of Rule	MF of Error	Degree of Rule	MF of Error	Degree of Rule	MF of Error	Degree of Rule
0	-2.990	0.505	-1.843	0.922	-1.784	0.892	1.554	0.777	0.662	0.669
1	0.478	0.754	1.218	0.603	3.918	0.953	-1.312	0.643	7.422	0.985
11	2.018	0.928	-0.390	0.732	-5.773	0.777	-3.854	0.801	-1.807	0.779
12	-2.930	0.464	-1.229	0.523	-3.447	0.481	-2.775	0.290	-2.852	0.470
13	-2.088	0.723	-0.477	0.667	-2.289	0.668	-2.461	0.644	-1.114	0.382
14	-1.819	0.722	-1.069	0.433	-1.590	0.670	-1.166	0.812	-0.271	0.710
15	0.558	0.519	-1.062	0.399	-0.725	0.441	-0.957	0.432	0.540	0.564
16	0.994	0.326	1.253	0.400	1.111	0.204	2.824	0.387	1.289	0.429
21	-1.141	0.541	-2.020	0.872	-4.427	0.746	4.675	0.615	-3.735	0.750
22	-3.604	0.602	1.636	0.576	-2.199	0.710	-0.396	0.676	-7.823	0.631
23	11.969	0.895	5.237	0.551	10.851	0.783	-0.591	0.664	9.025	0.711
24	-0.854	0.517	-1.980	0.791	-1.095	0.479	-1.779	0.831	-1.026	0.445
25	-0.428	0.687	-0.996	0.394	0.523	0.580	2.118	0.871	1.890	0.883
27	-0.737	0.538	0.613	0.505	1.871	0.712	1.204	0.503	0.530	0.573
28	0.988	0.401	0.544	0.499	0.361	0.638	0.807	0.474	1.215	0.343
29	0.710	0.546	0.042	0.642	0.086	0.625	0.382	0.536	0.669	0.000
30	0.294	0.504	-0.042	0.979	0.000	1.000	0.000	1.000	0.294	1.000
33	-1.165	0.513	-2.365	0.816	-2.795	0.260	-1.067	0.472	-2.733	0.536
35	1.746	0.600	6.022	0.885	10.178	0.510	1.674	0.400	-1.239	0.400
37	-1.132	0.483	-0.560	0.684	-1.871	0.548	0.730	0.652	-0.866	0.473
38	-1.061	0.241	-1.983	0.544	-0.786	0.607	-0.009	0.682	-0.478	0.468
39	0.602	0.631	-0.381	0.746	-0.079	0.961	0.400	0.623	0.450	0.493
40	-0.405	0.798	-0.169	0.916	-0.039	0.980	0.000	1.000	-0.043	0.979

Table 3(2) Error Calibration of Operating Mode Bins Distributions

Operating Mode Bins	Driver 6		Driver 7		Driver 8		Driver 9		Driver 10	
	MF of Error	Degree of Rule	MF of Error	Degree of Rule	MF of Error	Degree of Rule	MF of Error	Degree of Rule	MF of Error	Degree of Rule
0	-1.801	0.777	-3.144	0.620	-0.443	0.882	-1.178	0.852	0.554	0.548
1	1.867	0.924	0.638	0.574	1.518	0.886	0.918	0.913	-1.831	0.864
11	-2.386	0.784	1.218	0.898	1.390	0.573	-2.773	0.872	-5.854	0.758
12	-1.326	0.509	-2.653	0.434	-1.529	0.452	-1.447	0.681	-1.775	0.659
13	-2.733	0.535	-2.551	0.693	-0.777	0.767	-0.289	0.437	-4.461	0.384
14	-2.965	0.440	-1.218	0.642	-2.069	0.643	0.590	0.767	-0.166	0.882
15	-0.866	0.388	0.233	0.479	0.062	0.740	-2.725	0.644	-0.547	0.613
16	1.646	0.525	0.429	0.456	2.253	0.640	1.711	0.720	2.612	0.567
21	-0.882	0.539	-1.541	0.681	-2.820	0.687	-3.427	0.897	3.275	0.861
22	-2.223	0.722	-2.204	0.652	1.036	0.858	-2.920	0.887	-1.840	0.768
23	1.421	0.627	5.969	0.955	3.237	0.756	5.851	0.908	0.131	0.544
24	0.685	0.537	-2.154	0.468	-2.598	0.891	-2.095	0.779	-1.279	0.971
25	1.766	0.838	-1.428	0.749	-0.796	0.794	-0.152	0.390	4.118	0.921
27	2.462	0.663	-0.125	0.699	0.613	0.611	0.871	0.641	3.002	0.453
28	0.474	0.508	0.149	0.513	2.154	0.429	1.361	0.838	1.481	0.674
29	0.000	0.000	0.991	0.666	0.142	0.442	0.056	0.425	0.582	0.336
30	0.000	1.000	0.988	0.720	-0.342	0.968	0.000	1.000	0.000	1.000
33	0.836	0.337	-3.565	0.353	-1.365	0.882	-2.279	0.426	-2.107	0.322
35	-0.354	0.586	1.025	0.757	1.022	0.585	4.178	0.410	1.017	0.724
37	5.340	0.578	-1.201	0.348	-1.560	0.784	-1.287	0.365	0.573	0.665
38	-0.933	0.419	-1.516	0.624	-2.983	0.594	-1.786	0.707	-0.007	0.768
39	-0.028	0.694	1.860	0.813	-0.181	0.875	-0.039	0.981	0.200	0.862
40	0.000	1.000	-0.805	0.855	-0.069	0.956	-0.059	0.980	0.000	1.000

Table 3(3) Error Calibration of Operating Mode Bins Distributions

Operating Mode Bins	Driver 11		Driver 12		Driver 13		Driver 14		Driver 15		Error(%)
	MF of Error	Degree of Rule	MF of Error	Degree of Rule	MF of Error	Degree of Rule	MF of Error	Degree of Rule	MF of Error	Degree of Rule	
0	0.687	0.967	-3.801	0.537	1.054	0.818	2.266	0.867	-1.080	0.688	**-1.802**
1	4.004	0.880	1.009	0.992	-0.312	0.856	5.042	0.599	-2.867	0.709	**0.750**
11	-1.287		-2.434	0.878	-4.185	0.901	-3.807	0.768	-4.039	0.978	**-1.847**
12	-2.152	0.545	-3.033	0.529	-1.075	0.490	-2.009	0.770	0.326	0.751	**-0.540**
13	-1.231	0.688	-0.733	0.775	-1.661	0.444	-1.891	0.538	-1.227	0.653	**-1.830**
14	-2.093	0.757	0.365	0.454	-0.166	0.512	-1.027	0.827	-1.030	0.344	**-0.437**
15	2.040	0.649	-1.119	0.664	-0.460	0.743	2.340	0.756	-2.019	0.739	**-1.484**
16	1.829	0.847	1.986	0.785	1.482	0.539	2.029	0.664	1.216	0.853	**0.628**
21	-1.013	0.645	-0.569	0.465	3.168	0.615	-1.735	0.817	-0.569	0.754	**1.537**
22	-1.023	0.523	-2.872	0.537	-1.896	0.868	-5.823	0.836	-1.822	0.567	**-2.192**
23	2.825	0.789	1.824	0.826	-0.519	0.466	4.203	0.871	1.642	0.896	**1.502**
24	-3.883	0.971	2.685	0.454	-1.079	0.783	-1.526	0.814	0.547	0.425	**0.532**
25	1.881	0.518	1.166	0.784	3.418	0.519	3.890	0.688	3.468	0.784	**-1.578**
27	0.993	0.347	4.466	0.817	1.910	0.580	1.153	0.857	1.746	0.766	**1.820**
28	1.012	0.544	1.874	0.651	0.581	0.747	0.515	0.783	0.985	0.588	**0.636**
29	0.067	0.988	0.000	0.000	1.738	0.654	1.669	0.566	0.000	0.000	**0.287**
30	0.333	0.832	0.000	1.000	0.000	1.000	0.094	0.997	0.000	1.000	**0.031**
33	0.577	0.715	0.596	0.437	-2.467	0.347	-0.273	0.836	1.584	0.434	**-0.823**
35	-1.024	0.245	-1.354	0.786	2.074	0.840	-3.224	0.740	-1.735	0.759	**3.110**
37	-1.017	0.485	4.340	0.878	0.173	0.765	2.087	0.547	3.834	0.858	**2.625**
38	-0.103	0.865	1.933	0.919	-0.109	0.868	-1.478	0.347	-0.533	0.342	**-0.877**
39	0.030	0.955	-0.128	0.894	0.200	0.862	0.220	0.749	-0.088	0.969	**0.091**
40	-0.023	0.989	0.000	1.000	0.000	1.000	-0.043	0.979	0.000	1.000	**-0.140**

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Operating Mode Distributions

Twenty drivers participated in the experimental tests, resulting in 1,140 kilometers' driving and 90,260 second-by-second speed and acceleration data recorded from both the real world and driving simulator testing experiments. The participating drivers included 13 males and 7 females who were students or faculty members at Texas Southern University, University of St. Thomas-Houston, Rice University, and Texas Medical Center. After calculating VSPs and generating operating mode distributions, frequencies of operating mode IDs were plotted for the data from both the real-world driving and the driving simulator, as shown in Figure 7. The figure shows the average frequencies in 23 defined operating mode bins for 20 drivers.
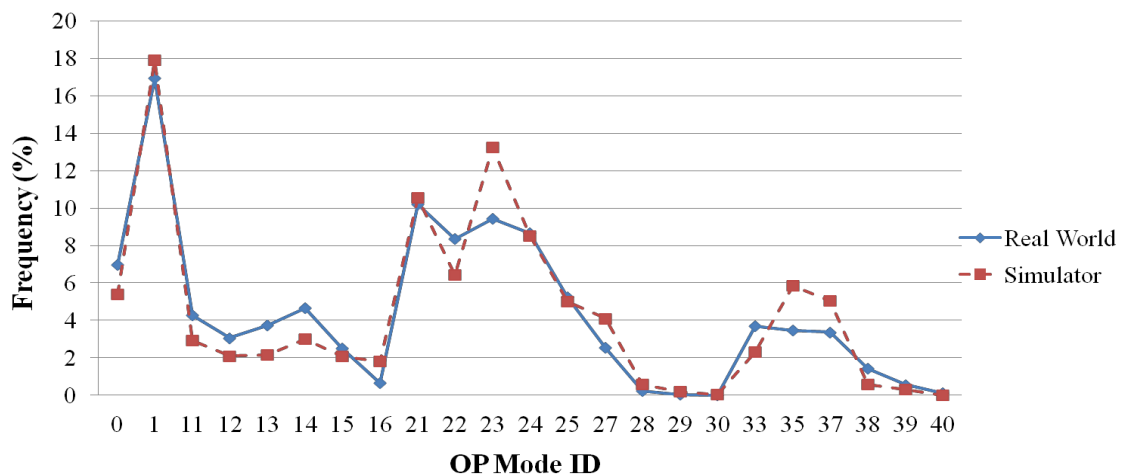

FIGURE 8 Average Frequencies in Operating Mode Bins for 20 Participating Drivers

Figure 8 shows that frequencies for most of the operating mode bins for real world and driving simulator tests are very similar, as were the curve trends. This indicates

high probability that total emissions for two scenarios may also be close. Nevertheless, for several specific IDs such as "23,"the average error is as high as 4%.In order to explore the cause of this error, an analysis on bin-by-bin was conducted. There are 20 groups of data results from 20 participating drivers. For each group, the frequency of each operating mode ID was calculated for both the driving simulator and the real world tests. The error was calculated as the difference between the frequency from the driving simulator and the frequency from the real world test (see Figure 9).
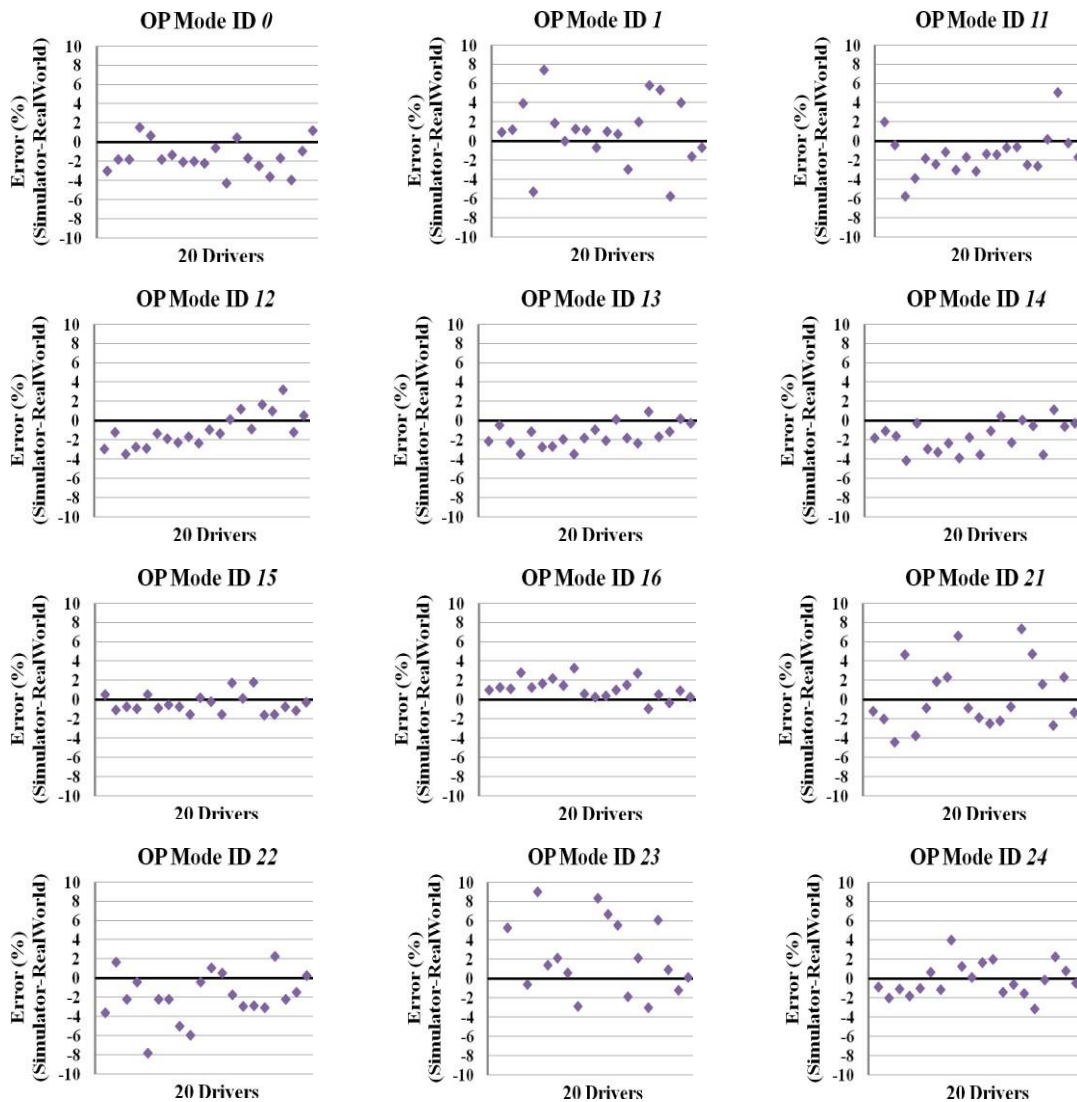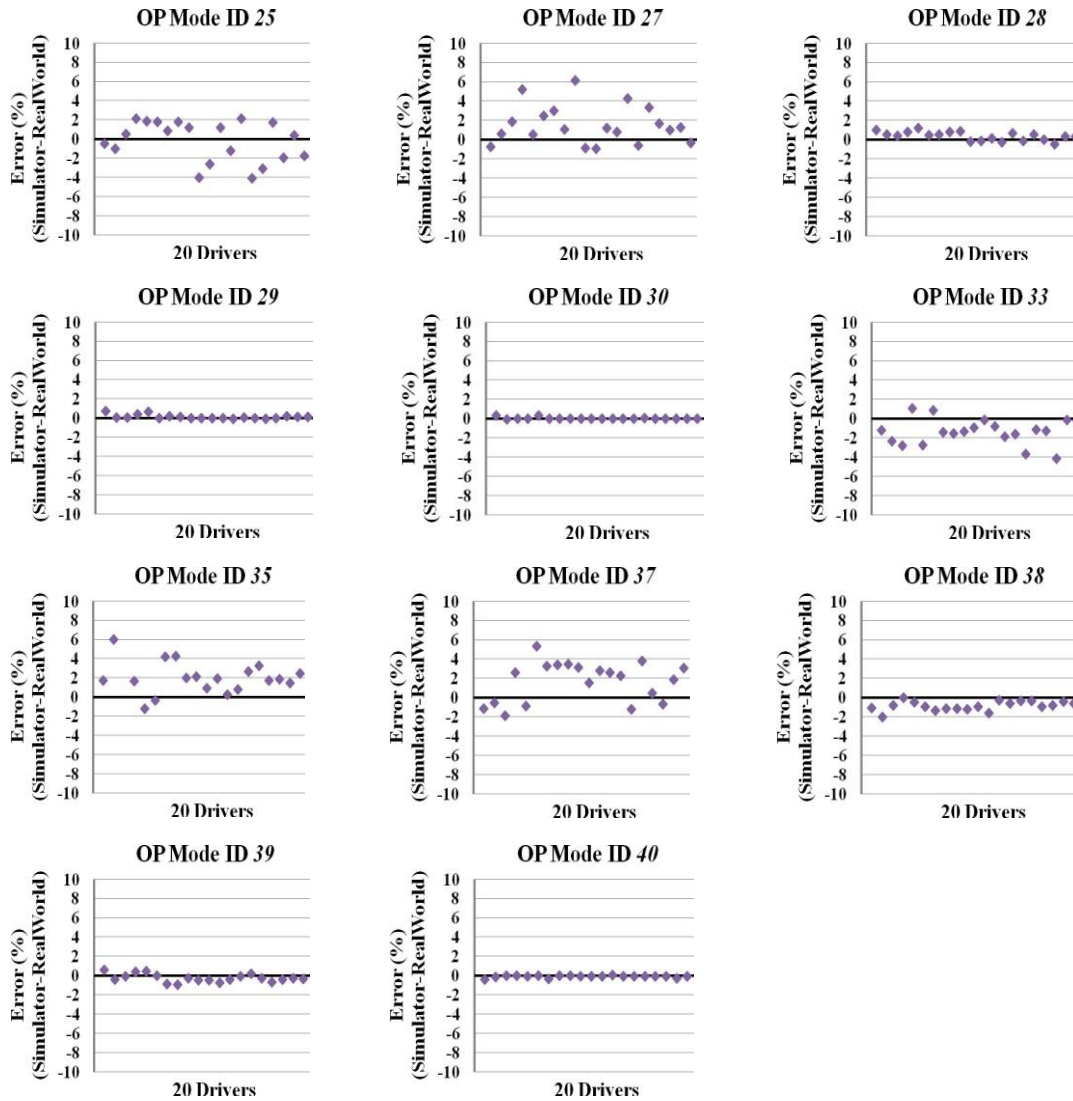
FIGURE 9 Error of Operating Mode Distributions in Each Bin

According to Table 1, ID0 represents the low deceleration, where errors for most of drivers are negative, meaning that the frequency from the driving simulator is lower. In another interpretation, when the car is slowing down, the driver in the driving simulator may apply a larger deceleration rate. This is possibly because the braking system of the driving simulator is not as smooth as that of a real car, thus causing a large deceleration rate when slowing down.ID1 indicates that the car is idling. In the driving simulator, since the deceleration tends to be larger, the car has to stop more quickly. Therefore, the

stopping time at the intersection is longer, resulting in positive errors for ID1. For all IDs11 to16 and IDs21 to30 that have the same speed, the VSP value gradually increases, as shown in Table 1. It is interesting to observe that with the increase of the ID number, errors transition gradually from negative to positive, which means that the frequency from the driving simulator is lower than that from the real world when VSP is low, but higher when VSP is high. This observation shows that at the same speed range, the driving simulator always produced more high VSP data than did the driving simulator. Further, for IDs28 to 30 and IDs 38 to 40, frequencies are already very small (less than 1% of all samples); therefore, the result is unlikely to affect the total emissions.

Based on the drivers' feedback on the questionnaire survey that was conducted immediately after the driving test, 90% of drivers concurred that driving in the simulator was not much different from driving on real roads. They did not meet any technical or operational problems. However 100% of the drivers also agreed that it was easier to get dizzy in the driving simulator during the test, which was a major technical difference between the real world driving and simulator driving. Further 65% of the participating drivers pointed out that after 15 to 20 minutes driving on the simulator, they could hardly focus their attentions on their driving. Therefore, the driving simulator seems not to be appropriate for a long time test, as it may cause the driver to respond more slowly to high speed changes than would be the case in a short time period. Another survey result showed that 75% of the participating drivers felt that the brake and accelerator in the driving simulator were more sensitive than those in the real car were. As a result, for both starting and stopping actions, the accelerations and decelerations in the driving simulator tended to be always higher than those in the real car were; thereby the VSP also increased

in the driving simulator. The last feedback was that 65% of the participating drivers agreed that driving in the driving simulator was smoother because there were not many distracting factors around. As a result, the average travel time for each driver in the driving simulator was 2,176 seconds, which was shorter than the 2,337 seconds for the real world driving on the same route.

The above analysis explains very well why there was an error between the results from the driving simulator and the real world, and why the driving simulator had higher frequencies for operating mode IDs with higher VSP values while the results were the opposite in the real world scenarios.
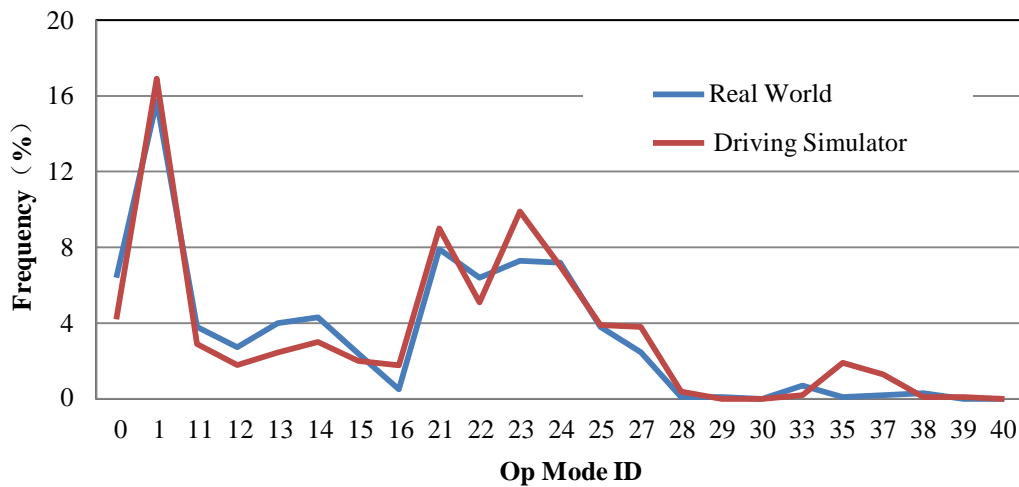
4.2 Freeway and Local Road

The previous section considered the different data features between the real world and driving simulator. This section will explore in depth the differences between freeway and local road driving.

In the scenario of this study, the distances travelled on the freeway and local road are almost the same. The second-by-second data from real world and driving simulator is separated into two parts, based on the road type. The comparison results are shown in Figure 10.
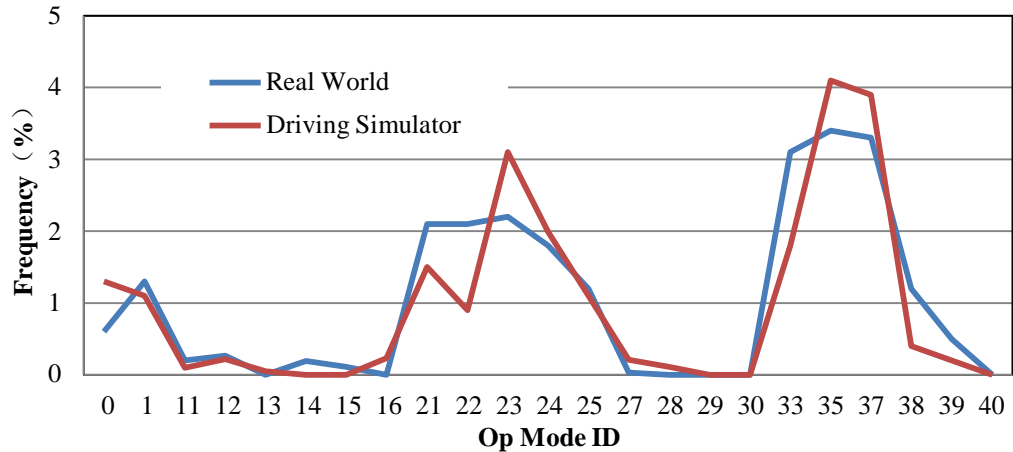
(a) Freeway

(b) Local Road

FIGURE 10 Frequency of Each ID on Freeway and Local Road

The frequency of second-by-second data on local road is much higher than that on freeway, because for the same distance, the travel time on freeway is shorter. For the freeway, most data spreads over the middle and high-speed part. On the contrary, the local road has more idling and low speed data. However, unlike the real world, the driving simulator has some high-speed data on the local road. That is because the simulator accelerator is easy to speed up, and its traffic conditions and others' driving

behavior on the local road are much better than in the real world. The drivers always drove faster on local road during the test.

Figure 11 shows the relative difference frequency of each ID between the real world data and driving simulator data on freeway and local road.
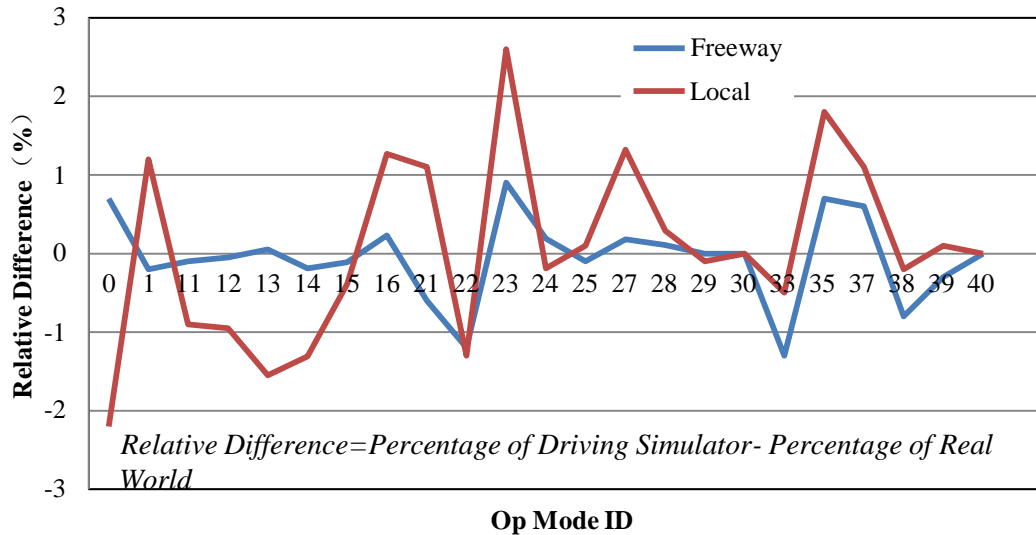

FIGURE 11 Relative Difference of Each ID on Freeway and Local Road

From the Figure above, it is clear to see that the relative differences of each ID on the freeway are much closer to 0 than those on the local road. The average relative difference of all IDs on freeway is only 0.37%, while on local road it is more than double (0.89%). This result makes it clear that most differences between real world and driving simulator data come from the local road. Because the drivers have to accelerate and decelerate frequently on the local road, they cannot make these speed changes smoothly during the simulator test; that is the major cause of the difference.

Another result points out that for the freeway, the total frequency from the driving simulator is only 22.3% less than the 23.6% from the real world. As the driving simulator

tests always have less travel time, after multiplied by the frequency, the travel time in the driving simulator becomes much shorter on the freeway. This is mainly because the drivers are not afraid to speed in the fictitious environment, thus, they may pay less attention to the speed limit control, leading to the higher speed and shorter travel time.

4.3 Verification

In order to examine whether the differences of operating mode distributions between real world and driving simulator tests are acceptable, the correlation analysis was conducted by using the Statistical Product and Service Solutions (SPSS) software. Average frequencies in each operating mode bin, derived from real world and simulator tests, were used as the input to SPSS.

4.3.1 Correlation Analysis

Correlation presents a relationship between two variables. A strong and high correlation means the two or more variables have a strong relationship with each other. On the contrary, a weak and low correlation means the variables are not likely to be related. Correlation coefficients can range from -1.00 to +1.00. The value of -1.00 represents a perfect negative correlation while a value of +1.00 represents a perfect positive correlation. The value of 0.00 indicates that there is no relationship between the variables being tested.

Correlation analysis is used mainly to test hypotheses about cause-and-effect relationships. For this kind of condition, the experimenter determines the values of the X-variable and explores whether variation in X causes variation in Y. It can also be used for

correlation and regression is to see whether two variables are associated, without necessarily inferring a cause-and-effect relationship. In this case, neither variable is determined by the experimenter; both are naturally variable. If an association is found, the inference is that variation in X may cause variation in Y, or variation in Y may cause variation in X, or variation in some other factor may affect both X and Y. Another application for correlation analysis is using linear regression to estimate the value of one variable corresponding to a particular value of the other variable.

This study considered the cause-and-effect relationship between the two different conditions of the data. Pearson correlation coefficient was used in this research, and "two-tailed" was selected for the significance test. The results were shown in Figure 12, with the correlative coefficient of 0.95 and the significance level of 0.01.
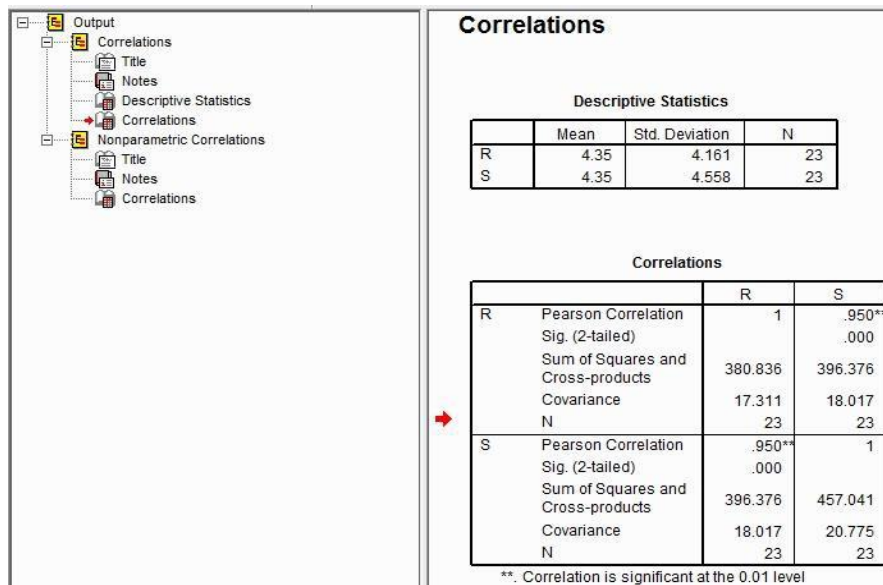

FIGURE 12 Correlation Analysis

4.3.2 Significance Test

Statistical significance is the probability that an effect is not due to just chance alone. It is an integral part of statistical hypothesis testing, where it is used as an important value judgment. In statistics, a result is considered significant not because it is important or meaningful, but because it has been predicted as unlikely to have occurred by chance alone. The present-day concept of statistical significance originated from Ronald Fisher when he developed statistical hypothesis testing in the early 20th century. These tests are used to determine which outcomes of a study would lead to a rejection of the null hypothesis, based on a pre-specified low probability threshold called p-value, which helps an investigator decide if a result contains sufficient information to cast doubt on the null hypothesis. P-values are often coupled to a significance or alpha (α) level, which is also set ahead of time, usually at 0.05 (5%). Thus, if a p-value was found to be less than

0.05, the result would be considered statistically significant.

However, significance testing was difficult to apply for the distributions. For this situation, only the IDs with larger differences (ID 23, 35 and 22) were chosen for analysis. If the results are good, the other IDs with fewer differences should have the same results. A paired t-test was used for this study to compare two population means where there were two samples, so that observations in one sample could be paired with observations in the other sample. Results are shown in Table 4. For all three pairs, the significance was larger than 0.05, which means the differences were indistinctive. Thus, the conclusion can be made that the difference between these two distributions is indistinctive.

Table 4 Paired T-Test Results

Paired Samples Test

		N	t	Sig.
Pair 1	Simu23 & Real23	20	4.616	.052
Pair 2	Simu35 & Real35	20	7.347	.180
Pair 3	Simu22 & Real22	20	-6.204	.073

4.4 Total Emissions

Based on the binning standard in MOVES, emission rates for each operating mode bin were derived, as shown in Table 5.

Table 5 Light Duty Vehicle Emission Rates in Operating Mode Bins

OPModeID	CO_2 (g/s)	CO (mg/s)	HC (mg/s)	NO_x (mg/s)
0	1.008	8.889	1.111	0.833
1	0.894	9.444	0.833	0.833
11	1.373	11.111	0.833	1.111
12	1.820	19.167	0.833	2.500
13	2.678	31.389	1.389	5.278
14	3.562	46.389	1.667	9.167
15	4.386	52.222	2.222	12.778
16	5.563	61.667	2.500	17.778
21	1.715	21.389	1.111	3.056
22	2.116	23.333	1.111	3.611
23	2.738	28.889	1.111	5.278
24	3.579	44.167	1.667	8.889
25	4.574	46.111	1.944	12.222
27	6.033	81.389	2.778	20.556
28	8.131	128.056	4.444	32.222

29	11.144	273.889	7.500	46.111
30	13.946	786.111	12.500	54.167
33	2.707	17.500	1.111	3.889
35	4.303	35.278	1.667	11.111
37	5.603	47.500	1.944	16.667
38	7.305	120.556	3.889	27.500
39	9.724	180.556	4.167	36.667
40	12.431	389.167	5.556	48.333

Based on the travel time and the emission rate in each operating mode ID, total emissions were estimated by Equation (2) to validate the applicability of the driving simulator for the emissions analysis. Equation (3) was used to calculate relative differences of total emissions between real world and driving simulator tests. According to Equation (3), emissions generated by the driving simulator were higher than those from the real world when the value was positive, and vice versa. As illustrated in Table 6, total emissions from the real world and the driving simulator were around 5% for each pollutant, only HC was larger than 5%. However, emissions derived from the driving simulator were generally higher than those from the real world, except for NO_x.

$$E_x = t_0 \times r_{x0} + t_1 \times r_{x1} + t_2 \times r_{x2} + \cdots + t_{40} \times r_{x40} \qquad (7)$$

where:

E: total emissions;

x: type of emissions, CO_2, CO, HC, or NO_x;

t: travel time in each ID; and

r_{x_n}: emission rate of emission type x in operating mode ID n.

$$\text{Relative difference} = \frac{E_S - E_R}{E_R} \times 100\%$$

where:

E_S: emissions from the driving simulator;

E_R: emissions from the real world.

Table 6 Total Emissions of Testing Scenarios

	Total Emissions			
	CO_2 (g)	CO (mg)	HC (mg)	NO_x (mg)
Real world	6386.03	72257.21	3250.56	14198.89
Driving Simulator	6193.41	69067.26	3066.15	14895.14
Relative differences	-3.016%	-4.415%	-5.673%	4.904%

4.5 Calibrated Results

In order to validate the calibration result, the other five groups of data are analyzed. In addition to the vehicle activity data, there are also real world and driving simulator operating mode bins distributions, for which the driving simulator distributions can be calibrated by the membership functions calculated before, to generate the new calibration distributions. Figure 13 shows the comparison of three average distributions of those five drivers.
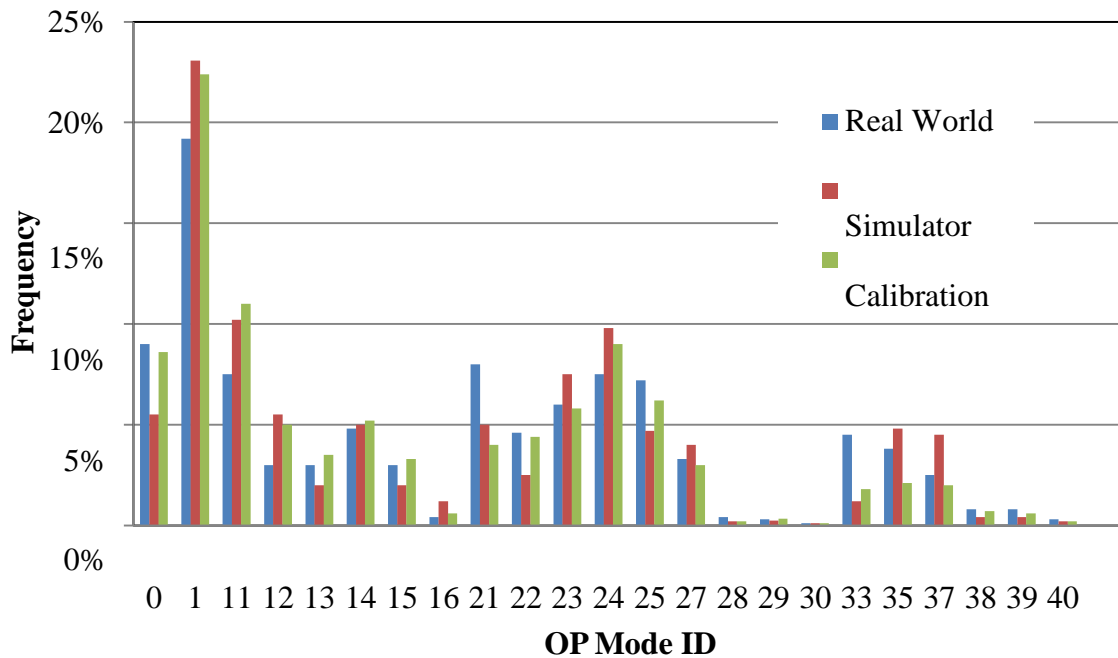
FIGURE 13 Comparison of the Average Three Distributions

The result shows that for more than two-thirds of the bins, the simulated percentage is closer to the real one after it is calibrated, which means the Fuzzy Logic calibration can be used for the driving simulator data in general. However, validation is still needed for whether all the emissions have the same condition and whether the error is reduced so that this method can be used in emission estimation. Based on the definition of the operating mode-based approach in Table 1 and the emission rates for each bin in Table 5, the study explored in more detail the relative differences for CO_2, CO, HC and NO_X before and after calibration. The results are shown in Figure14.
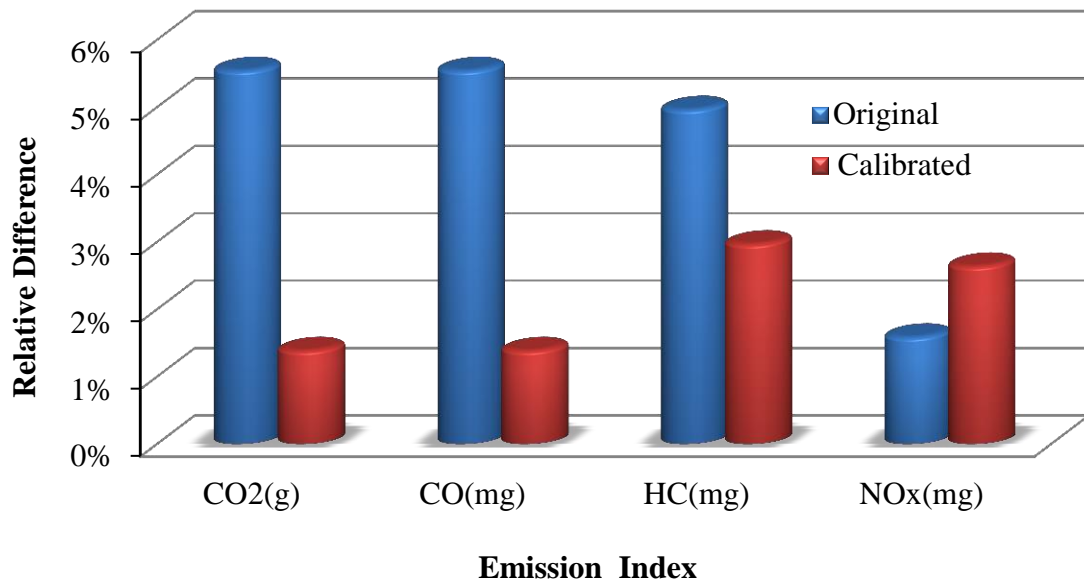
FIGURE 14 Average Absolute Relative Differences in Emissions

For the emissions CO_2, CO and HC, after calibration, the relative differences are observably lower. However, the original relative difference of NO_X is already less than 2%; therefore, the calibrated result for NO_X is unsatisfactory.

CHAPTER 5

CASE STUDIES

5.1 Vehicle Emissions in Traffic Conflicting Areas

In recent years, many Intelligent Transportation Systems (ITS) based technologies have been proposed and applied on roads for safety purposes (Li et al., 2015c; Munni et al., 2015; Rahman et al., 2015). In the same time, the implications of these technologies on vehicle emissions become critical for sustainable transportation. In this section, the vehicle emissions in a traffic conflicting area that are equipped with a Vehicles to Infrastructure (V2I) facility, including a work zone and a signalized intersection with sun glare disturbance, are estimated using the propose simulator approach.

5.2 Scenarios Design and Tests

A total of thirty subjects were recruited for the driving simulator tests, which selection was based on Houston's demographics from 2010 census. The proportion of subjects regarding gender, age, and education background was adjusted for the legal driving age in the U.S. Fifteen male and fifteen female subjects aged above eighteen years old with valid C class drive licenses participated in the test. More specifically, twenty-six subjects were between the ages of eighteen and sixty-four, while four subjects were seniors aged sixty-five plus. Twenty-one subjects had obtained high school and/or associated degrees, and nine subjects achieved bachelor's degree or higher. All subjects have self-reported that they have normal or corrected-to-normal vision, and do not have

any   problems   with   hearing.

For the tests in the traffic conflicting area of a work zone, subjects drove twice through a short-term work zone with two lanes in one direction for different scenarios: with static traffic control signs and both of sign control and the V2I system (see Figure 15). The posted speed limit was changed from 72 km/h (45mph) to 48 km/h (30mph or 13.33m/s) when approaching the work zone. In the activity area of the work zone, subjects may encounter a sudden crossing of a pedestrian. With the V2I system, drivers received audio warning and/or instructive messages, except the static control signs. More specifically, subjects received an audio message at the distance of 70 meters and 107 meters for a traffic sign and a risk warning, respectively. These distances considered stop distance instructed by 2009 MUTCD and the reaction-time 2.5 seconds (Li and Qiao, 2014). Drivers 'operation data were collected and calibrated by the designed Fuzzy logic based Look-Up Scheme for the estimation of vehicle emissions.
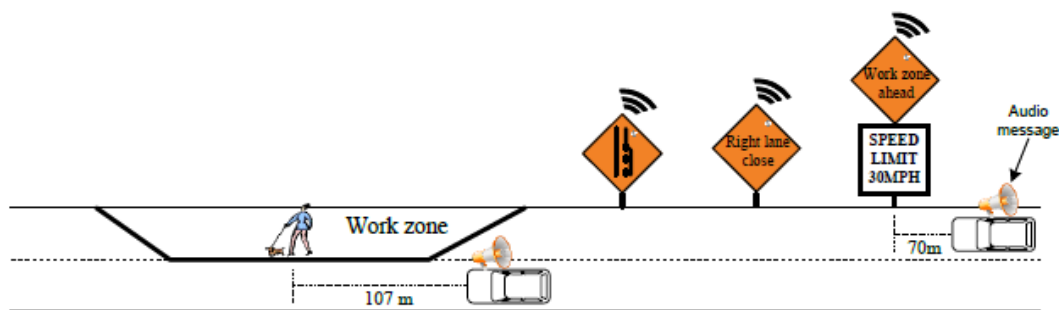

FIGURE 15. Layouts of Two Scenarios (with and without Audio Messages)

For the tests in the traffic conflicting area of a signalized intersection, a track of approximately 1,000 meters in an industrial area with three intersections was generated in scenarios (see Figure 16). The distance between intersections is about 300 meters, while the posted speed limit is 72 km/h (20m/s). Each subject was the only driver on the track.

Subjects were required to drive through the three intersections in three different situations: no sun glare no V2I (base), with sun glare no V2I (S-V2I), and with sun glare and V2I (S+V2I).

With the V2I system, drivers received audio messages about the real-time signal, while approaching a signalized intersection under a visual disturbance of sun glare. The location subjects received audio messages depends on the play time of the message (1 sec), driving speeds, perception-reaction time, and minimum sight distance for signal visibility. 2.5 seconds was chosen as the perception-reaction time. The minimum sight distance was 140 meters for the posted speed limit 72 km/h (20 m∕s) (MUTCD, 2009). Therefore, drivers received the audio message at 210 meters away from the third intersection ((1.0+2.5) ×20 m/s+140 m=210 m). Similarly, the vehicle activities in the three scenarios were collected and calibrated by the designed Fuzzy logic based Look-Up Scheme for estimating vehicle emissions.
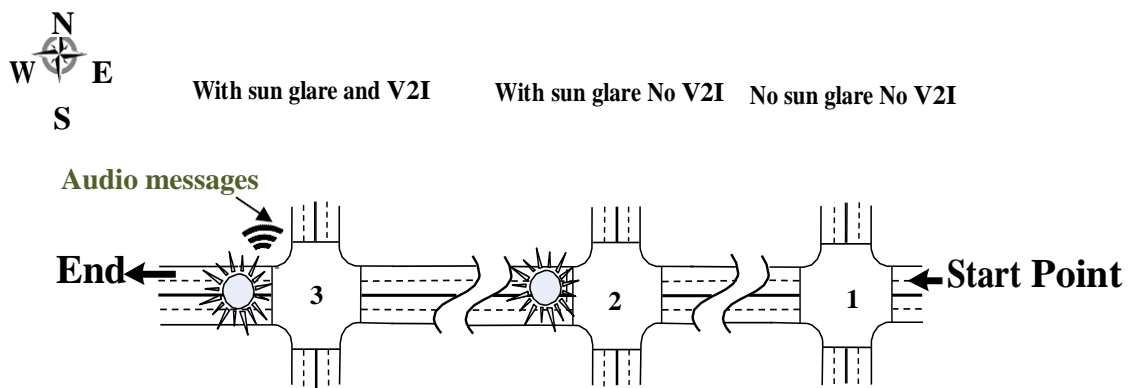
FIGURE 16. Layout of Test Route with and without V2I and Sun Glare

5.3 Vehicle Emissions Estimation

Figure 17 illustrates the comparison of vehicle emissions estimated in the scenarios with and without the aid of V2I system, while driving through a work zone with a sudden pedestrian's crossing. Obviously, with the V2I system, vehicles emit less emission. The four main emission indexes (CO_2, CO, CO_x and HC) reduced apparently, particularly the CO_2 emissions. Approximately 350 gram per vehicle in total is emitted, which is 24% less than the emission caused by a vehicle with no V2I system.
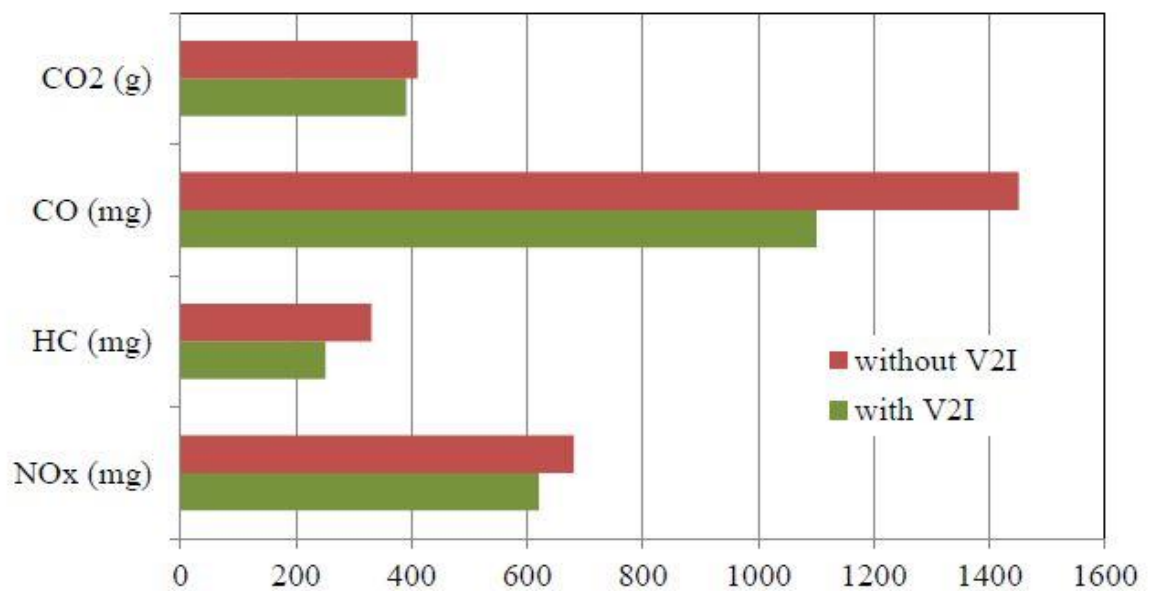

FIGURE 17. Vehicle Emissions with and without V2I Warning System

Regarding the hazardous situation at the test intersections, the estimated emission rates are compared among the three scenarios and shown in Figure 18.
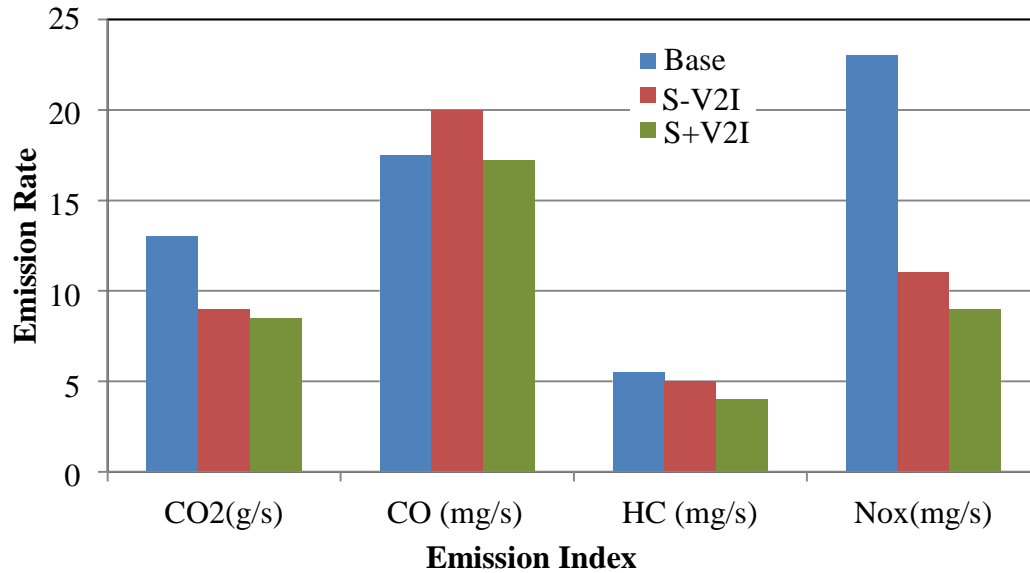
FIGURE 18. Vehicle Emission Rates Related to Driving Directions at Intersections

In Figure 18, except CO, the emission rates of the CO_2, NO_x, and HC in the base scenario (no sun glare and no V2I system) are higher than the others by 20% to 80%. This implies that in a normal situation to approach a signalized intersection, a vehicle emission is higher than the situation under visual disturbance. As a contrary, the emissions rates under a sun glare without V2I are slightly lower. However, seven of the thirty (23%) subjects ran red-light unconsciously, as some of them were either too late to stop or could not realize the upcoming signalized intersection due to the visual impairment of sun glare. It can be imagined that the emissions rates could be lower without idling, braking or excessive acceleration. Surprisingly, with the aid of V2I system, the emissions rates were significantly lower than others. This phenomenon is acceptable, since the V2I system provides subjects with audio instructions to drive safer and smoother. For the CO emission, the emission rate under a sun glare effect without the V2I system is the highest, while there is rare difference found in the situations between

the base scenario and the scenario without the V2I system (S-V2I). CO is one of byproducts for incomplete fuel combustion during an excessive acceleration (Li et al., 2016), which indicates that the V2I can instruct drivers to driving smoothly, thereby lowering vehicle emissions.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

Based on the two groups of driving activity data collected from the real world and the driving simulator, this study conducted a comparative analysis of operating mode distributions to determine whether the data derived from the driving simulator can be reliably used to estimate vehicle emissions. The study found that operating mode distributions from the two groups showed similar trends, and the errors for individual operating bins were relatively small. Then, total emissions were compared to verify further the feasibility of using driving simulator data for vehicle emission estimations.

Several conclusions can be drawn from the study:

1. Results from the statistical tests suggested that operating mode distributions between the driving simulator and real-world tests were highly correlated. This showed that driving in the driving simulator was not much different from driving a car in the real world. This is good news for those who plan to use the driving simulator to study operating mode distributions.

2. Results of the analysis showed that the driving simulator tended to produce higher VSPs than did the real world. In the two operating mode distributions, the driving simulator produced high frequencies for IDs with high VSP values. Further, because of the frequent acceleration and deceleration, driving in the driving simulator resulted in less deceleration time but longer stopping time.

3. The biggest difference between the operating mode distributions of real world versus driving simulator tests was about 4%, while the difference between corresponding

4. Emission rates were also up to 4%. These errors only occurred for several specific IDs and emission types.

5. The difference mainly pertained to the local road. For the freeway, the data from the driving simulator was much closer to the real world. This was because on the local road, the traffic conditions were more complicated and there were more accelerations and decelerations.

6. Drivers' feedback explained well why the acceleration and deceleration were high in the driving simulator. First, driving a long time in the driving simulator environment tended to lead to dazzle, resulting in slow responses to certain conditions such as sudden stops. In addition, the accelerator and brake in the driving simulator were more sensitive than those in the real car, As a result, when the driver attempted to speed up with the same power as they usually apply in a real-world driving situation, the acceleration would be too high.

7. Two case studies demonstrated that it is applicable to estimate vehicle emissions using the driving simulator test combined with the Fuzzy logic based Look-Up Scheme calibration, and the estimated emission results were relative reasonable.

Further research is recommended to focus on the following issues:

1. A greater number of drivers from different groups of age, gender, and driving experience should participate in the test to explore factors that influence the results of testing in the driving simulator.

2. More tests should be conducted to validate further whether the driving simulator data can be used for vehicle emission estimations. It would also be useful to develop a

method to calibrate the data from the driving simulator to be more representative of real world conditions.

3. It is suggested to find different calibration methods for both freeway and local roads that could make the results more accurate.

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